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Forecasting Freight Rates:

Evidence from the Baltic Exchange Indices and the IMAREX Freight Futures

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Abstract

Forecasting freight rates is of great importance to ship owners, charterers, commodity and energy producers. This dissertation examines the forecasting ability of the Baltic Exchange Indices and the IMAREX freight futures. Point and interval forecasts are constructed and assessed under different statistical measures. In order to give a firm answer, trading strategies based on point and interval forecasts are performed using IMAREX Freight Futures and evaluated under performance measures.

Keywords: Freight markets, Freight Rates, IMAREX Futures, Interval Forecasts, Forecasting, Bootstrap, Economic Significance, Shipping.

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Chapter 1

Introduction

The shipping industry is responsible for the 80% of the world merchandise trade. The freight rate is the cost of hiring/leasing of this transportation (chartering). This dissertation focuses on the most popular dry and wet spot and futures freight markets and addresses the question whether spot and futures freight rates can be forecasted.

Forecasting spot freight rates is of great importance to ship owners, charteres, academics and practitioners. Freight markets' main characteristics are cyclicality, extreme volatility, seasonality and exposure to international business environment. Fluctuations in freight rates affect shipowners' cash flows, charterers' costs and commodity and energy producers. Forecasting futures freight rates is of great importance too. Participants of the maritime industry can hedge their cash flows through the futures freight market. Furthermore, examining the freight futures market is interesting, since the underlying asset traded in freight futures markets is a service rather than a storable commodity. This means that arbitrage between spot and futures markets is not possible, since spot and forward prices are not linked by the rigid cost-of-carry relationship. Along with the thinness of the futures market and the absence of a strong speculative interest, we conclude that futures markets may not be moving to the same direction with the underlying spot freight rates due to information incorporated into the futures price.

Modelling, and therefore forecasting, spot and futures freight rates in the dry bulk and tanker shipping have been a topic of much research in maritime economics. Researchers have focused on modeling the freight rates in a traditional demand and supply framework in line with the classical literature. In the late 1980s and early 1990s, Beenstock and Vergottis published a series of papers in which they developed an integrated econometric model of the spot dry and tanker cargo markets, Beenstock and Vergottis (1989a) and Beenstock and Vergottis (1989b). To the best of our knowledge, these two studies are the most recent fully specified structural econometric work. The key feature of this work is the seminal development of a coherent explanation of ship price behavior, which is grounded in the application of the two basics hypothesis of rational expectations of freight prices and market efficiency. The freight rate is determined by the proportional difference between quantity demanded and the supply of ship services. Other studies that use economic variables to explain the behavior of spot freight rates are the following: Jonnala, Fuller and Bessler (2002) examined major factors that affect ocean spot freight rates for grain. They used autoregressive conditional heteroskedastic error processes in the specification and estimation of an ocean grain rate equation. The authors used a wide data set of economic variables that offer explanation of ocean freight rates. Their empirical model was tested for its forecasting ability against a random-walk model. Kavussanos and Alizadeh (2002) examine the determinants of spot tanker prices and their relationship with oil prices. Tanker freight rates are determined by the nature of trade in commodities vessels involve and supply special characteristics. The authors conclude that deterministic seasonal patterns exist, which are investigated through Markov Regime Switching Seasonal models. The seasonal models were tested for their forecasting abilities, up to 12 months ahead. Poulakidas and Joutz (2009) examine the relationship between weekly spot tanker prices and the oil market from 1998 to 2006, using cointegration techniques and Granger causality. They find a feedback between the spot tanker market (TD4 route – West African to US Gulf Coast), West Texas Intermediate crude oil spot prices and crude inventories. They conclude that spot tanker market is related to the crude oil prices, in such a relationship that higher oil prices put upward pressure on spot tanker rates. In addition, higher inventories put downward pressure on spot tanker rates.

The forecasting performance of spot freight rates was examined by the following studies. Cullinane (1992) argues that accurate short-term forecasts of spot rates can assist in the development of a forecasting model for short-term BIFFEX[1] speculative strategies. By deriving a Box-Jenkins autoregressive integrated moving average model of the BFI, covering the period between 1985 and 1988, he argues that predictions of movements in the BFI would seem to be as a basis for the development of a speculative strategy in the value of the nearby BIFFEX contract. Cullinane, Mason and Cape (1999) apply the Box-Jenkins ARIMA methodology in order to test whether the exclusion of all Handysize trades from the Baltic Freight Index (BFI) in November 1993 has altered its underlying behavior. Finally, the first study that used a

[1] In 1985 the first freight futures contract termed BIFFEX (Baltic International Freight Futures Exchange) in introduced in the London International Financial Futures Exchange (LIFFE). BIFFEX was written on the Baltic Freight Index (BFI). LIFFE terminated the trading of the BIFFEX contract in April 2002.

new approach in modeling ocean freight rates was the one of Veenstra and Franses (1997). The authors studied monthly spot freight rates for three capesize and three panamax routes. Based on formal statistical tests and cointegration techniques, they formulated a VEC model and evaluated its forecasting ability.

However, due to the revolution in econometric techniques, the empirical work has shifted in a new direction. This new direction is testing the performance of time series models in predicting spot and futures (or forward) rates on major freight routes or indices simultaneously using cointegration techniques. Glen (2006) provides a survey on the modeling of the dry bulk and tanker markets over the last fifteen years.

Chang and Chang (1996) examined the forecasting ability of BIFFEX and suggested that forecasts of the BFI can be employed to develop a strategy for speculation. The authors using regression analysis between BFI and BIFFEX prices, concluded that BIFFEX prices can predict movements of the dry bulk shipping market up to six months with an accuracy ranging from 90% in the case of a one-month lag to 23% in the case of a six-months lag. Furthermore, Kavussanos and Nomikos (1999) and Haigh (2000) investigated the unbiased role of the BIFFEX contracts. The first study finds that one-month and two-month BIFFEX contracts were unbiased estimators of the rates prevailing in the spot markets, while the second study find three-month BIFFEX contracts also to be unbiased estimators. Furthermore, the first study examined the ability of the BIFFEX contracts to predict spot prices for up to three-month contracts.

Kavussanos (2002) argues that, after using overlapping forecast intervals to compare joint VECM forecasts of spot freight rates and BIFFEX futures freight rates with forecasts from ARIMA, VAR and Random Walk models, the VECM generates the most accurate forecasts of spot prices but not of BIFFEX prices. Kavussanos and Nomikos (2003) investigate the casual relationship between futures and spot prices in the freight futures markets. They have found that the information incorporated in futures prices, when formulated as a VECM, produces more accurate forecasts of spot prices than the VAR, ARIMA and random-walk models, over several steps ahead. Kavussanos, Visvikis and Menachof (2004) investigated the unbiased role of the Forward Freight Aggrements, using cointegration tests. The results indicate that FFA prices one and two months before maturity are unbiased predictors of spot freight rates for all shipping routes under investigation. Three months FFA prices only for panamax Pacific routes are unbiased predictors of spot prices. Kavussanos and

Visvikis (2004) investigated the lead-lag relationship in returns and volatilities between spot and FFA prices. Batchelor et al. (2007) compare the performance of multivariate VAR, VECM, SURE-VECM and univariate ARIMA time-series models in generating short-term forecasts of spot freight rates and FFA prices for several Panamax routes. They have found that VECM models give the best in-sample fit and forward rates do help to forecast spot rates. Kavussanos and Visvikis (2006a) provide a thorough survey on freight derivatives research.

Finally, the focus the most recent literature has been on modeling the freight rate directly in a univariate stochastic model. A brief description of these studies follows. Adland and Cullinane (2005) concluded that the risk premium in bulk freight rates must be time varying, based on qualitative arguments. Adland and Cullinane (2006) use a general non-parametric Markov diffusion model to investigate the dynamics of the tanker freight rates. They also show that freight rates are mean reverting. Adland and Strandenes (2007) develop a fully representation of stochastic supply and stochastic demand in order to simulate the probability distribution of the future spot freight rates. Tvedt (2003) tries to bridge the gap between traditional equilibrium modelling and recent maritime asset pricing literature. The author develops a theoretical dynamic partial equilibrium model that includes the supply and demand for crude oil transport and the shipbuilding market. He concludes in a geometric mean reverting price process. Furthermore, Lyridis et al. (2004) using monthly data and Artificial Neural Networks (ANNs) try to forecast spot VLCC freight rates, while Goulielmos and Psifia (2009) use 'nonlinear dynamic' and 'chaotic' modeling to forecast weekly freight rates for a 65.000 dwt bulk carrier.

This dissertation makes some contributions to the ongoing discussion of the predictability of ocean freight rates in several points.

First, both point and interval forecasts are formed and evaluated. It is the first time that interval forecasts are constructed in freight markets. The literature previously mentioned has only considered point forecasts. We use a wide variety of econometric specifications and a wide variety of GARCH-type models for forecasting purposes.

Secondly, this dissertation employs an extensive data of freight indices. Previous literature is focused in certain routes or certain index. It is the first time that four barometer spot freight indices are evaluated simultaneously for forecasting purposes.

Third, since BIFFEX stopped functioning in 2001, it is the first time that IMAREX freight futures are used in the maritime literature to the best of our knowledge. This dissertation employs an extensive and unique data set of IMAREX freight futures. Furthermore, Kavussanos and Nomikos (1999, 2003) and Kavussanos and Visvikis (2004) have found that freight futures reveal information about the underlying spot freight rates, examining the joint forecasting performance of spot and futures prices. We address the question whether freight futures can reveal information about future movements in freight futures.

Finally, we assess the economic significance of the statistical evidence through trading strategies in the IMAREX futures based on point and interval forecasts. Trading strategies have been conducted by other studies too, but it is the first time that they are assessed by performance measures.

This dissertation is structured into six further sections. A brief description of the freight market and the data series used in the analysis are presented in Chapter 2. Chapter 3 describes the econometric specifications of the forecasting models. Chapter 4 presents the forecasting methodology and the statistical and economic evaluation. Chapter 5 discusses the results concerning the forecasting models on Baltic Exchange Indices and chapter 6 on IMAREX Futures. The last chapter concludes the dissertation.

Chapter 2

Description of the Market and Properties of the Data Series

2.1 Segmentation of the Freight Market

Maritime transport remains the backbone of international trade with over 80% of the world merchandise trade by volume carried by the sea, according to the United Nations Conference on Trade And Development (UNCTAD). Given this economic importance, a brief review of the ocean freight market must be held for better understanding the mechanisms of the industry and therefore of freight rates. It can be easily imagined that the bulk cargo market is a highly segmented one. Freight depends on the size of the vessel (e.g. tankers, bulk carriers and container ships), the type of the cargo that is carried, the route that is followed, delivery period and the type of chartering. Considering all these points, bulk cargoes are mainly involved in the transportation of raw materials, where each vessel carries one only material. Bulk cargoes are further sub-divided into liquid cargo and dry cargo. Liquid cargo includes crude oil, oil products, chemicals and wine. Dry cargo is divided into three broad categories: i) Majors: iron ore, coal, grain, bauxite and phosphates. ii) Minors: steel, steel products, cement, sugar, salt, sulphur, forest products etc. iii) Specialist bulk cargoes, requiring specific handling or storage requirements such as heavy lift, cars, refrigerated cargo and timber.

The vessels involved in bulk cargo transportation are tankers, dry-bulk carriers, combined carriers (they carry either dry or liquid bulk) and specialist bulk vessels. Bulk cargoes constitute approximately 2/3 of seaborne trade movements, and are carried mainly by tramp vessels, which constitute about 3/4 of the world's merchant fleet. These are vessels which move around the world, seeking employment in any place/route of the globe. Bulk vessels usually carry one cargo in one vessel, at rates negotiated individually, between the shipowner and the charterer, for the service provided. Dry cargo, including bulk and containerized cargo, accounted for the largest share of goods loaded (66.6%) while oil made up the balance, as can be seen in the figure 1. The rest of the seaborne trade share belongs to the tanker trade. In 2007, world shipments of tanker cargoes reached 2.68 billion tons, of which more than two thirds were crude oil.

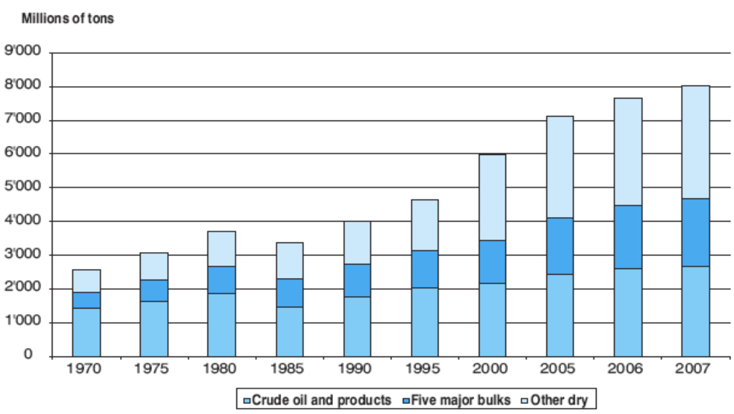
General cargo, is also dry cargo, in general, but not transported in bulk. A large part of general cargo is transported in containers, multipurpose and other specialized vessels (RoRo, car carriers, etc.). General cargo, which constitutes the 1/3 of seaborne trade, moves in either tramp vessels or liners. Liners provide a regular, scheduled service transporting small cargo consignments at fixed tariff levels. Table 1 summarizes the world fleet size segmentation by principal types of vessels.

Dry and liquid bulk cargoes can be further subdivided according to the vessel size. Physical port limitations on vessel size draw a line between groups. The main vessel groups according to their size are Capesize, Aframax, Handysize, etc. This is because size determines the type of trade the vessel will be involved in, in terms of type of cargo and route. Certain vessel groups are involved in transporting certain commodities. This is a result of the different commodity characteristics and port restrictions for certain size vessels. For instance, Capesize vessels are involved in transporting either iron ore or coal, as described below. Design features are important, such as, cargo handling gear, pumping capacity and segregation of cargo tanks in tankers.

Figure 1

International seaborne trade for selected years

(Millions of tons loaded)



Source: UNCTAD *Review of Maritime Transport*, various issues.

Dry-bulk sub-market is segregated according to their tonnage capacity in three main categories: Capesize, Panamax and Handy groups. Capesize vessels (100.000 – 180.000 dead-weight tons (dwt)) transport iron ore, mainly from South America and Australia to Japan, West Europe and North America, and coal from North America and Australia to Japan and Western Europe. Panamax vessels (50.000 – 80.000 dwt) are used primarily to carry grain and coal from North America and Australia to Japan and west Europe. Handysize vessels (10.000 – 24.999 dwt) and Handymax vessels (25.000 – 49.999 dwt) transport grain, mainly from North America, Argentina and Australia to Europe and Asia. Furthermore, they transport minor bulk products, such as sugar, fertilizers, steel and scrap, salt from over the world.

Table 1

World fleet size by principal types of vessel

Vessel types	2005	2006	2007	2008
Oil tankers	336	354	383	408
Bulk carriers	320	346	367	391
General cargo ships	92	96	100	105
Containerships	98	111	128	144
Other type of ships	49	52	62	68
Total (millions dwt)	**895**	**959**	**1040**	**1116**

Source: Review of Maritime Transport 2008

The operation of Capesize vessels is restricted due to their deep draught and limited number of commodities that they can transport. Capesize ships are too large to traverse the Suez or Panama canals and must round the Cape of Good Hope or Cape Horn to travel between oceans, while the term “capesize” is most commonly used to describe bulk carriers rather than tankers. Panamax vessels are the largest vessels that can pass through the Panama Canal. The size is limited by the dimensions of the lock chambers and the depth of the water in the canal. Due to the lack of cargo handling gears and deep draught, panamax ships are not so flexible, thus transporting few commodities. Finally, Handymax and Handysize vessels are mainly engaged in grain transportation and minor dry-bulk commodities around the world. Due to their smaller size, relatively shallow draught and the existence of cargo handling gears on board, they are flexible to switch between shipping routes and types of commodities, if weak market conditions prevail.

Liquid-bulk sub-market is divided in Ultra Large Cargo Carriers (ULCC), Very Large Cargo Carriers (VLCC), Suezmax, Aframax, Panamax and Handy groups. ULCC vessels (320.000 + dwt) and VLCC vessels (200.000 – 319.999 dwt) vessels transport crude oil from Middle East to US East Coast, West Europe and Far East. Suezmax vessels (120.000 – 199.999 dwt) carry crude oil from Middle East to US East Coast, West Europe and Mediterranean. According to Kavoussanos (2003) 60% of crude oil trades are carried by VLCC vessels and 30% from Suezmax vessels.

Moreover, they transport cargo from the North Sea and deliver it to US East Coast and from West Africa to US and Europe. Aframax, Panamax and Handy can carry not only crude oil, but "dirty" and "clean" products as well. "Dirty" Products are crude oil, fuel oils, asphalt, etc. and "clean" products are refined products such as gasoline, jet fuels, kerosene, etc. "Clean" products are mainly transported by Panamax and Handy vessels.

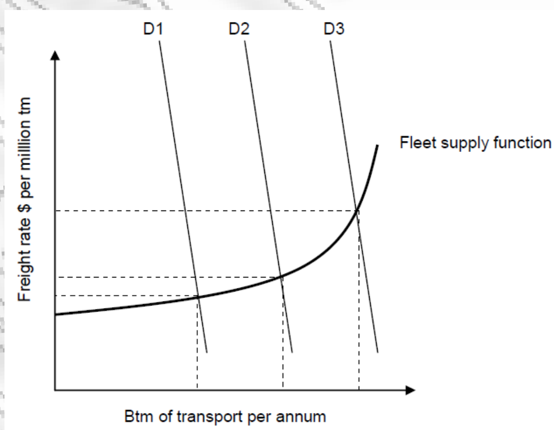
2.2 Equilibrium Freight Rates

Freight rates in the shipping freight markets are determined from the demand and supply for freight services. Demand for freight services is referred for the service that a vessel offers. Demand is considered inelastic, since the cost of transportation is relatively low to the final price of the transported good.

Supply for freight services has the shape observed in figure 2 and varies through different stages of a business cycle. Fleet size and laid-up tonnage are specific factors of the shipping industry and are closely linked to the equilibrium of supply and demand for seaborne trade and therefore with the determination of the freight rates.

Figure 2

The Shipping Freight Market



The aggregate deadweight tonnage of active ships comprising the dry bulk or tanker fleet is included as the major supply factor of shipping service. Due to the fact that many years are often required to construct a ship, the total supply is almost fixed in the short run. However, in the long run, new vessels are built and added to the fleet, shifting the entire supply curve to the right. Furthermore, vessels may be sent for scrap or lost through accidents. The net effect in the stock of the fleet depends on the balance between vessels delivered and vessels scrapped or lost. If deliveries exceed scraping and losses, the entire supply curve shifts to the right, resulting in lower freight rates for a given level of demand.

Laid up tonnage includes the total deadweight tonnage of bulk carriers laid-up due to inadequate demand. In periods of recession when the market is weak, vessels are laid up because no remunerative employment can be found and market conditions make it uneconomic to trade. Conversely, in periods of prosperity when the market is strong, there is little or no laid up tonnage and freight rates are sustained in high levels. The greater the capacity of laid up vessels, the lower the freight rates will be. The variable, therefore, is expected to be negatively related to freight rates.

Therefore, equilibrium freight rates are determined at the intersection of the demand and supply in the market. When the market is weak, a decrease or increase in the demand curve has a small influence on freight rates. At the top of the supply curve, when the market is strong, a decrease or increase of the same magnitude has a large influence on freight rates.

These conditions have been shown to hold empirically in studies such as Kavussanos and Alizadeh (2001, 2002).

2.3 Baltic Exchange

Due to this wide market segmentation, the Baltic Exchange publishes a large number of indices on a daily basis. The Baltic Exchange is a membership organisation at the heart of the global maritime marketplace, with a total membership of over 550 companies and 2000 individuals. The company was founded in 1744 under the name *Virginia and Baltick Coffee House*. Since its foundation is located in the city of London. The Baltic Exchange is the world's only independent source of maritime market information for the trading and settlement of physical and derivative contracts. This organization appoints panel reporting companies, which are assigned the task of reporting freight rates to the exchange on a daily basis. These data are then used by the Baltic to build its freight rate indices, which it reports to the market. Baltic market information is published at the 13:00 London time from Monday to Friday for all dry-bulk indices and 16:00 London time for Dirty and Clean tanker indices. The reliability of the freight rate indices depends greatly on the members of the panel. Thus, Baltic Exchange appoints panel reporting companies in accordance with the following criteria (Baltic Exchange, 2009):

• The main business of panellists should be shipbroking. Principals are not considered appropriate panelists.

• Panellists must be recognised as competent, professional firms, actively engaged in the markets they report, with adequate personnel to perform the role of panellist .

• Panellists must be members of the Baltic Exchange, fulfilling all relevant membership criteria.

• Panellists must agree to be bound by the standard terms set out by the Baltic Exchange

• An appropriate geographical spread of panellists is maintained.

• The Baltic seeks to avoid the appointment of panellists who are the exclusive representatives of charterers who are particularly influential in relevant trades.

• Panel reporting companies must nominate a Principal or Representative member of the Baltic as responsible for each index they report on.

2.3.1. Composition of the Dry-Bulk Freight Rates Indices

In January 1985 the Baltic Exchange launched its Baltic Freight Index (BFI), in order to construct a benchmark index of the cost of transporting dry bulk commodities. Furthermore, BFI consisted the underlying asset needed to write a futures contract on, in contrast to other commodity markets, where the underlying asset is a commodity. To be specific, Baltic International Freight Futures Exchange was an exchange for trading ocean freight futures contracts with settlement based on the BFI. Since its introduction, Baltic Exchange has altered the composition of the BFI in order to be in line with developments in the dry-bulk sector of the shipping industry.

On 1st of November 1999, Baltic Exchange introduced the Baltic Dry Index (BDI), which is the successor to the Baltic Freight Index (BFI). In a move designed to help boost derivative trading, the Baltic Exchange revised the composition of the index in the 1st of July 2009. Since this last revision, BDI is a composite of the Capesize, Panamax , Supramax and Handysize Timecharter Averages. The calculation until the 30th of June 2009 was based on an equally weighted average of the BCI, BPI, BHSI and the BSI index, which superseded the BHMI on 03 January 2006, which superseded the BHI on 2 January 2001. Each vessel type's routes make up 25% of the BDI.

Table 2 shows the composition of the Baltic Capesize Index. It comprises spot and time-charter routes, coded C2 to C12, involving vessel sizes, which range from 150.000 dwt to 172.000 dwt, carrying iron ore and coal in the routes described. Furthermore, the weights assigned to each route reflect the importance of the route in the composition of the index.

Table 2
Baltic Capasize Index - Route Definitions

Routes	Vessel Size (dwt)	Route Description	Weights
C2	160,000	Tubarao to Rotterdam	10%
C3	160,000	Tubarao to Qingdao	15%
C4	150,000	Richards Bay to Rotterdam	5%
C5	160,000	W. Australia to Qingdao	15%
C7	150,000	Bolivar to Rotterdam	5%
C8 TC	172,000	Delivery Gibraltar–Hamburg range, 5–15 days ahead of the index date, transatlantic round voyage duration 30–45 days, redelivery Gibraltar–Hamburg range	10%
C9 TC	172,000	Delivery Amsterdam-Rotterdam-Antwerp or passing Passero, 5–15 days ahead of the index date, redelivery China–Japan range, duration about 65 days	5%
C10 TC	172,000	Delivery China–Japan range, 5–15 days ahead of the index date, round voyage duration 30–40 days, redelivery China–Japan range	20%
C11 TC	172,000	Delivery China–Japan range, 5–15 days ahead of the index date, redelivery Amsterdam-Rotterdam-Antwerp or passing Passero, duration about 65 days	5%
C12	150,000	Gladston to Rotterdam	10%

Source: Baltic Exchange

Table 3 shows the composition of the Baltic Panamax Index. Just as with the BCI, the table describes the routes, the vessel size and the weights assigned to each route, reflecting the Panamax market in 2009.

Table 3
Baltic Panamax Index - Route Definitions

Routes	Vessel Size (dwt)	Route Description	Weights
P1A	74,000	Transatlantic (including east coast of South America) round of 45/60 days on the basis of delivery and redelivery Skaw–Gibraltar range	25%
P2A	74,000	Basis delivery Skaw–Gibraltar range, for a trip to the Far East, redelivery Taiwan-Japan range, duration 60–65 days	25%
P3A	74,000	Transpacific round of 35/50 days either via Australia or Pacific (but not including short rounds such as Vostochy (Russia)/Japan), delivery and redelivery Japan/South Korea range	25%
P4	74,000	Delivery Japan/South Korea range for a trip via US West Coast—British Columbia range, redelivery Skaw–Passero range, duration 50/60 days	25%

Source: Baltic Exchange

2.3.2. Composition of the Tanker Freight Rates Indices

The Baltic Exchange launched in January 1998 the Baltic International Tanker Route (BITR) index, in an effort to create an independent index for the tanker freight markets also. Besides providing a barometer of how tanker freight rates changed over time, the BITR and its constituent route indices served as the underlying assets, upon which tanker freight derivatives can be settled. On 1 August 2001, the Baltic launched two new indices: the Baltic Dirty Tanker Index (BDTI) and the Baltic Clean Tanker Index (BCTI). This modification came in recognition of the fact that ‘dirty’ and ‘clean’ markets are separate entities, thus must be treated accordingly. These indices are calculated as the simple average of the dirty and clean routes that comprise the indices. The Baltic Exchange has made changes and expansions on the two tankers indices. In contrast to dry-bulk freight rates that are expressed in US$/ton, tanker freight rates are reported in Worldscale (WS) units. “Worldscale Tanker Nominal Freight Scale”, more commonly known as “Worldscale”, was created in 1969, to introduce a more convenient way of negotiating freight rate pre barrel of oil. From 1969 until 1988, Worldscale was regularly revised for changes in bunker prices and port costs. On 1st January 1989 the “New Worldscale” was introduced. However, the epithet "new" was soon dropped and now it is generally understood that “Worldscale” refers to the new scale. “Worldscale” is the joint endeavour of two non-profit making organisations know as Worldscale Association (London) Limited and Worldscale Association (NYC) INC. Tables 4 and 5 describe the compositions of the Baltic Clean Tanker Index and the Baltic Dirty Tanker Index respectively, as they stood in 2009.

Table 4
Baltic Clean Tanker Index - Route Definitions

Routes	Vessel Size (dwt)	Route Description	Vessel
TC 1	75,000	Middle East Gulf to Japan: Ras Tanura to Yokohama	Aframax
TC 2_37	37,000	Continent to USAC: Rotterdam to New York	Handysize
TC 3_38	38,000	Caribbean to USAC: Aruba to New York	Handysize
TC 5	55,000	Middle East to Japan: Ras Tanura to Yokohama	Panamax
TC 6	30,000	Algeria to Euromed: Skikda to Lavera	Handysize
TC 8	65,000	AG to UK-Cont: Jubail to Rotterdam	Panamax
TC 9	22,000	Baltic to UK-Cont: Ventspils to Le Havre	Handysize

Source: Baltic Exchange

Table 5
Baltic Dirty Tanker Index - Route Definitions

Routes	Vessel Size (dwt)	Route Description	Vessel
TD 1	280,000	Middle East Gulf to US Gulf : Ras Tanura to Loop	VLCC
TD 2	260,000	Middle East Gulf to Singapore: Ras Tanura to Singapore	VLCC
TD 3	260,000	Middle East Gulf to Japan: Ras Tanura to Chiba	VLCC
TD 4	260,000	West Africa to US Gulf: Off Shore Bonny to Loop	VLCC
TD 5	130,000	West Africa to USAC: Off Shore Bonny to Philadelphia	Suezmax
TD 6	135,000	Black Sea to Mediterranean: Novorossiyk to Augusta	Suezmax
TD 7	80,000	North Sea to Continent: Sullom Voe to Wilhelmshaven,	Aframax
TD 8	80,000	Kuwait to Singapore: Mena al Ahmadi to Singapore	Aframax
TD 9	70,000	Caribbean to US Gulf: Puerto La Cruz to Corpus Christi	Panamax
TD10	50,000	Caribbean to USAC: Aruba to New York	Panamax
TD11	80,000	Cross Mediterranean: Banias to Lavera	Aframax
TD12	55,000	Amsterdam-Rotterdam-Antwerp range to US Gulf	Panamax
TD14	80,000	SE Asia to EC Australia	Aframax
TD15	260,000	West Africa to China	VLCC
TD16	30,000	Black Sea to Mediterranean: Odessa to Augusta	Handysize
TD17	100,000	Baltic to UK-Cont: Primorsk to Wilhelmshaven	Aframax
TD18	30,000	Baltic to UK-Cont:Tallinn to Rotterdam	Handysize

Source: Baltic Exchange

2.4 International Maritime Exchange (IMAREX)

International Maritime Exchange (IMAREX) is a professional freight derivatives exchange for the global maritime industry, founded in spring 2000, as a joint venture by Herman W. Michelet, a former Platou Shipbrokers partner and Frontline, I.M. Skaugen ASA, RS Platou AS and NOS Holdind ASA, all Norwegian public limited companies. The Oslo-based IMAREX utilizes mostly the indices built by the Baltic Exchange but also some indices from Platts, to write freight rate derivatives upon. It is accepted by the US Commodity Futures Trading Commision to operate an electronic trading facility as an Exempted Commercial Market (ECM).

Table 6

Accumulate trades through IMAREX and NOS

Total	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**
Number of Transactions	672	4.393	6.256	9.929	15.968	20.304	18.203
Number of Lots	35.396	247.324	188.727	246.098	398.084	450.909	430.638
Value ($ million)	$ 405	$ 4.361	$ 3.342	$ 6.623	$ 15.206	$ 17.846	$ 9.224

Source: IMAREX

Following extensive market consultation, the company launched a complete marketplace for freight derivatives and partnership agreements on technology and exchange operation were established. It started operating on 2 November 2001. Its focus during the first half of 2002 was to establish a critical mass of trading and clearing members in the tanker segment, while later on the same year, operations extended to the dry cargo market. In partnership with the Norwegian Options and Futures clearing house (NOS) – offering its clearing services – IMAREX has become an authorized and regulated marketplace for trading and clearing shipping freight derivatives. At IMAREX you can trade Freight Futures, Freight Options, OTC Freight Forwards (FFAs) and Bunker fuel oil derivatives, as well as Index Futures on the Baltic Dry Index (BDI). Its trading hours are during all business days, from 09:00 to 18:30 Central European time. IMAREX is closed for trading on UK public holidays. Trading can be facilitated directly on the IMAREX trading screen. Table 6 provides an indication of the number of transactions, number of lots and value of transactions in US$ million for the total derivatives trades. It is easily noticeable that volume trading gradually ascends.

Table 7
Summary of Contract Details of IMAREX BDI Derivatives

Underlying	**Index** Baltic Dry Index - BDI
Price quotation	USD
Minimum price fluctuation	USD 1
Contract value	# Lots x Lot size x Price
Delivery Period	**Month:** First Index Day of the Month to last Index Day of the Month. **Quarter:** First Index Day of the Quarter to last Index Day of the Quarter. A Quarter Contract will be split equally into 3 Month Contracts on the Trading Day and settled as Month Contracts. **Year:** First Index Day of the Year to last Index Day of the Year. A Year Contract will be split equally into 12 Month Contracts on the Trading day and settled as Month Contracts.
Final Settlement Day	Last settlement day in the Delivery Period.
Settlement Price	The average of Spot Prices for the relevant Underlying Product in the Delivery Period
Lot size	1 lot = 1
Minimum lots per contract	0.01 lots
Clearing Fee	4$ per lot

Source: IMAREX

Tables 7 summarizes the contract details of IMAREX BDI derivatives. The minimum price fluctuation is 1$, price quotations are in US$ and the clearing fee is 4$ per lot. The minimum lots per contract are 1 lot for Month contracts, 3 lots for Quarter contracts and 12 lots for Year contracts. IMAREX members can trade derivatives for 4 consecutive months, 4 consecutive quarters and 4 year contracts.

Tables 8 summarizes the contract details of IMAREX Tanker derivatives. The minimum price fluctuation is 0.25 Worldscale points, price quotations are in WS and the clearing fee is 0.35% of the contract value. The minimum contract size is 1.000 dwt for Month lot, 3.000 dwt for Quarter lot and 12.000 dwt for Year lot. IMAREX members can trade derivatives for 6 consecutive months, 6 consecutive quarters and 2 year contracts.

Tables 9 summarizes the contract details of IMAREX Dry Bulk T/C Basket derivatives. The minimum price fluctuation is 25$, price quotations are in US$/Day and the clearing fee is 0.25% of the contract size. The minimum lots per contract are 1 lot for all contracts. IMAREX provides derivatives for 4 consecutive months, 4 consecutive quarters months, 2 consecutive half-year and 5 yearly contracts.

Table 8
Summary of Contract Details of IMAREX Tanker Derivatives

Underlying	**Index** TD 3, VLCC, AG – East, 260,000 mt TD 5, Suezmax, West Africa - USAC, 130,000 mt TD 7, Aframax, North Sea - Continent, 80,000 mt TD 8, Aframax, Kuwait – Singapore, 80,000 mt TD 9, Aframax, Caribs – USG, 70,000 mt TD11, Aframax, Cross – Med, 80,000mt TD16, MR, Black Sea – Mediterranean, 30,000mt TD17, Aframax, Baltic Sea – Continent, 100,000 mt TC 2, MR, Continent – USAC, 37,000 mt TC 4, MR, Singapore - Japan, 30,000 mt TC 5, LR 1, AG – Japan, 55,000 mt TC 6, MR, Algeria – Euromed, 30,000 mt
Flat Rates	As published by the Worldscale Association (London) Limited and the Worldscale Association (NY) Inc.
Price quotation	Worldscale points
Minimum price fluctuation	0.25 Worldscale point
Contract value	#Lots x Lot size x Worldscale Flat rate x (Worldscale points/100) (The Worldscale Flatrate applicable for each Index Day in the Delivery Period)
Delivery Period	**Month:** First Index Day of the month to last Index Day of the month. **Quarter:** First Index Day of the Quarter to last Index Day of the Quarter. A Quarter Contract will be split equally into 3 Month Contracts on the Trading Day and settled as Month Contracts. **Year:** First Index Day of the Year to last Index Day of the Year A Year Contract is split into equally into 12 Month Contracts on the Trading day and settled as Month Contracts.
Final Settlement Day	Last settlement day in the Delivery Period.
Settlement Price	The arithmetic average of the Spot Prices for the relevant Underlying Product over the number of Index Days in the Delivery Period.
Lot size	1 lot = 1,000 mt
Minimum lots per contract	0.01 Lot in all Products
Clearing Fee	0.35% of Contract Value

Source: IMAREX

Table 9
Summary of Contract Details of IMAREX Dry Bulk T/C Basket Derivatives

Underlying	**Index** CS 4 TC, Capesize, T/C Average PM 4 TC, Panamax, T/C Average HS 6 TC, Handysize, T/C Average SM 6 TC, Supramax, T/C Average
Price quotation	USD/day
Minimum price fluctuation	USD 25.00
Contract value	#Lots x Lot size x Price
Delivery Period	**Month:** First Index Days of month to last Index Day of month **Quarter:** First Index Day of the Quarter to last Index Day of the Quarter. A Quarter Contract will be split equally into 3 Month Contracts on the Trading Day and settled as Month Contract. **Half Year:** First Index Day of the Half Year to last Index Day of the Half Year. A Half Year Contract will be split equally into 6 Month Contracts on the Trading Day and settled as Month Contracts. **Year:** First Index Day of the Year to last Index Day of the Year. A Year Contract will be split equally into 12 Month Contracts on the Trading Day and settled as Month Contracts.
Final Settlement Day	Last settlement day in the Delivery Period.
Settlement Price	The arithmetic average of the Spot Prices for the relevant Underlying Product over the number of Index Days in the Delivery Period.
Lot size	1 lot = 1 day
Minimum lots per contract	1 Lot in all Products
Clearing Fee	0.25% of Contract Value

Source: IMAREX

2.5 Dataset

The dataset consists of daily prices of four Baltic Exchange Indices, a set of economic variables, a set of IMAREX futures and two variables for the valuation of trading strategies. The four Baltic Exchange indices are the Baltic Dry Index (BDI), the Baltic Capesize Index (BCI), the Baltic Panamax Index (BPI) and the Baltic Dirty Tanker TD3 Index (TD3), which is used to construct the Baltic Dirty Tanker Index. All four Baltic indices were described in Section 2.3 and obtained by Bloomberg. These indices are chosen because of their vital role in shipping industry, while they are representative indices of the freight market. The sample period is common for all variables, so as the econometric analysis can be comparable. The in-sample sub-period is from 5 April 2005 to 29 September 2006. The out-of-sample sub-period is from 2 October 2006 to 17 July 2009.

The economic variables dataset has been shown in previous studies to determine the demand for shipping services (see for instance, Beenstock and Vergottis (1989a, 1989b), Poulakidas and Joutz (2009), Kavussanos and Alizadeh (2002)). The economic variables are the following: i) West Texas Intermediate spot crude oil prices, which are obtained from the Energy Information Association. ii) S&P GSCI Grains Index Spot is the grain spot prices, provided by Bloomberg. The S&P GSCI Grains Index is part of the S&P GSCI Agriculture Index, which is a reliable benchmark for investment performance in the agricultural commodity markets. The index is calculated on a world production weighted basis, whereas the production weights are designed to reflect the relative significance of each of the constituent commodities. iii) Daily spot Coal prices provided by Bloomberg. iv) S&P GSCI Industrial Metals Index Spot is a basket of industrial metals prices, obtained by Bloomberg. S&P GCSI Industrial Metals index is a sub-index of S&P GSCI and provides investors with a reliable benchmark for investment performance in industrial metals. The index comprises five non-precious metals: Aluminum, Copper, Lead, Nickel and Zinc. Data are obtained by Bloomberg.

We use two more variables for the valuation of the trading strategies: FTSE ST Maritime Index and one month Libor interbank rate. The FTSE ST Maritime Index is part of the FTSE ST Index Series. It is produced jointly by Singapore Press Holdings, Singapore Exchange and FTSE Group. The index is designed for use as a performance benchmark, whereas it comprises 12 maritime related companies. Both indices are obtained from Bloomberg.

Finally, International Maritime Exchange (IMAREX) kindly provided a wide dataset[2] of Dry Bulk and Tanker Routes freight futures. The dataset for dissertation purposes consists of the four shortest futures maturities written on a Basket of four Time-Chartered Capesize routes (CS4TC), the four shortest futures maturities written on a Basket of four Time-Chartered Panamax routes (PM4TC) and the four shortest futures maturities written on the Dirty Tanker TD3 route. In order to minimize the impact of noisy data, we roll over to the next maturity contract five trading days before the contract expires. IMAREX futures specifications were analyzed in Chapter 2.4. The sample period of the IMAREX futures dataset is from 5 April 2005 until 17 July 2009.

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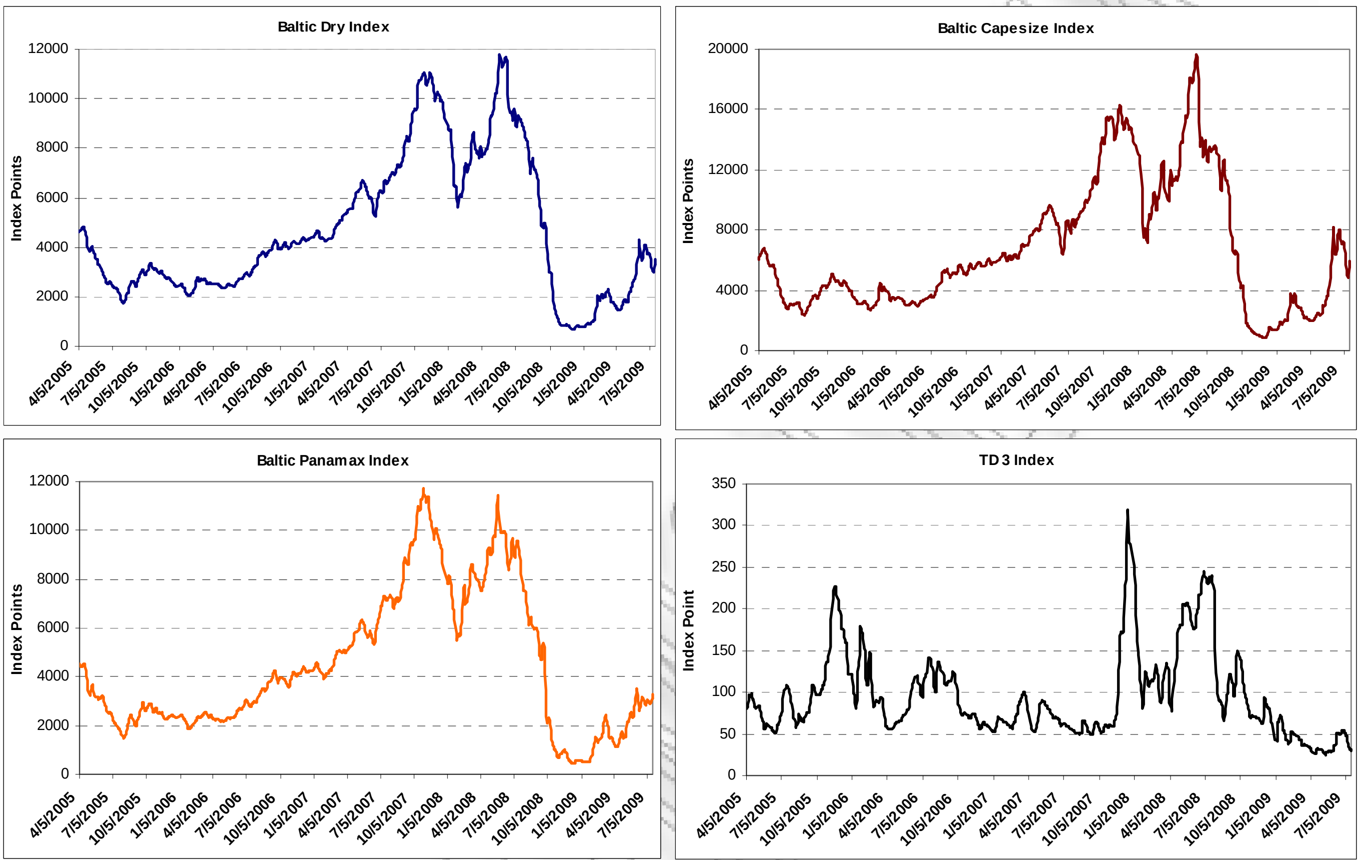
[2] IMAREX freight derivatives on Bloomberg could only be obtained since 2008.

Figure 3



Evolution of the Baltic Exchange Indices from 5 April 2005 to 17 July 2009

Figure 3 shows the evolution of the four Baltic Indices over the period 5 April 2005 to 17 July 2009. It is easily observed that BDI, BCI and BPI indices evolve in a similar manner, following similar patterns and cycles. These three indices reached their historical highs on May and June 2008. Thereafter, due to the world economic crisis, freight rates tumbled up to 96%, reaching extremely low values. Freight rates made record fall, due to extremely worldwide weak demand for commodities and the large amount of new ships deliveries, which put upward pressure on service supply and further downward pressure on freight rates. TD3 index has a downward trend due to weak demand for crude oil, since 2008. However, it seems to follow an independent path compared to the other Baltic indices.

Table 10 shows the summary statistics of the four Baltic Exchange indices, the performance indices and the commodity variables both in the levels and the differences. All variables found to be positively autocorrelated in the levels, as can be seen in table 10. Furthermore, extremely high autocorrelations have been found in the differences of the freight indices. These results indicate the use of ARMA methodology. Many economic time series exhibit trending behavior or non-stationarity in the mean. The Augmented Dickey-Fuller (ADF) test is estimated to examine the data series for unit roots, as described in Dickey and Fuller (1979). If the data series have a unit root, the data are non-stationary.

Three tests are conducted for this purpose, where each test differs in the assumed deterministic component in the series:

$$\Delta y_t = \alpha_i y_{t-1} + \sum_{i=1}^{P} \gamma_i \Delta y_{t-i} + \varepsilon_t \tag{1}$$

$$\Delta y_t = \alpha_0 + \alpha_i y_{t-1} + \sum_{i=1}^{P} \gamma_i \Delta y_{t-i} + \varepsilon_t \tag{2}$$

$$\Delta y_t = \alpha_0 + \alpha_i y_{t-1} + \alpha_2 * t + \sum_{i=1}^{P} \gamma_i \Delta y_{t-i} + \varepsilon_t \tag{3}$$

The first ADF form has no constant and trend, the second only constant and the third both constant and trend. The ε_t is assumed to be a Gaussian white noise error and t is a term for trend. P is the number of lags differences to ensure that the estimated errors are not serially correlated. P is chosen up to ten lags. The null hypothesis of the ADF tests is the existence of a unit root, and the alternative hypothesis is the non existence of a unit root.

Table 10
Descriptive statistics

Panel A: Baltic Exchange indices, Performace indices and Commodities (levels)											
	Baltic Dry	**Baltic Capesize**	**Baltic Panamax**	**TD3**	**FTSE ST Maritime**	**Libor 1 Month**	**Industrial Metals**	**Grain**	**Coal**	**WTI**	**Slope**
Mean	4680.9	6675.2	4464.1	94.85	460.24	3.16	365.91	344.46	60.98	72.49	0.46
Standard Dev	2815.8	4204.8	2842.9	51.25	222.25	1.14	100.78	118.08	20.93	22.93	1.14
Minimum	663	830	440	25.36	176.26	0.54	188.79	198.95	39.50	30.28	-1.5
Maximum	11793	19687	11713	319.22	1164.03	5.19	536.61	652.74	133.50	145.31	3.62
Skewness	0.77	0.91	0.74	1.42	1.1	-0.4	-0.31	0.68	1.62	1.2	0.81
Kurtosis	2.56	2.97	2.48	4.86	3.4	2.12	1.51	2.47	4.94	3.93	2.86
Jarque-Bera	**113.42***	**147.72***	**111.33***	**515.21***	**225.11***	**63.44***	**116.80***	**94.60***	**638.37***	**294.61***	**118.99***
ρ_1	0.999	0.998	0.999	0.994	0.998	0.997	0.996	0.997	0.995	0.996	0.994
ADF	-0.95	-1.15	-1.12	-1.84	-0.49	-0.65	-0.14	0.03	-0.62	-0.33	0.02
Observations	1073	1073	1073	1073	1073	1073	1073	1073	1073	1073	1073
Panel B: Baltic Exchange indices, Performace indices and Commodities (differences)											
Mean	-0.0003	0	-0.0003	-0.0009	0	-0.0013	0.0002	0.0004	-0.0001	0.0001	
Standard Dev	0.02	0.03	0.03	0.05	0.03	0.01	0.02	0.02	0.02	0.03	
Minimum	-0.12	-0.19	-0.22	-0.37	-0.17	-0.07	0.08	-0.09	-0.24	-0.13	
Maximum	0.14	0.17	0.13	0.30	0.12	0.14	0.11	0.08	0.22	0.34	
Skewness	-0.09	-0.08	-0.58	0.3	-0.15	1.18	-0.02	-0.24	-1.84	1.29	
Kurtosis	8.76	8.31	9.93	10.79	7.22	55.84	4.66	4.56	38.78	20.62	
Jarque-Bera	**1485.43***	**1261.22***	**2202.95***	**2728.08***	**798.04***	**124954.***	**123.11***	**119.23***	**57799.1***	**14165.1***	
ρ_1	0.843	0.768	0.838	0.611	0.092	0.503	-0.089	-0.015	0.006	0.014	
ADF	**-13.33***	**-14.92***	**-14.43***	**-13.74***	**-20.97***	**-12.63***	**-24.85***	**-23.18***	**-22.8***	**-23.87***	
Observations	1072	1072	1072	1072	1072	1072	1072	1072	1072	1072	

Entries report the summary statistics of each one of the Baltic Exchange Indices, Performance Indices and Commodity prices in levels (Panel A) and in the first differences (Panel B). The first order autocorrelation ρ_1, the Jarque-Bera and the Augmented Dickey Fuller (ADF) test values are also reported. One and two asterisks denote rejection of the null hypothesis at the 1% and 5% level, respectively. The null hypothesis for the Jarque-Bera and the ADF tests is that the series is normally distributed and has a unit root, respectively. The sample period is from 5 April 2005 to 17 July 2009.

The Augmented Dickey Fuller test indicates that all variables are stationary in the first differences at 1% level over the chosen period. One and two asterisks denote rejection of the null hypothesis at 1% and 5% respectively. Tables 10 and 11 report the ADF test results only for the first form. Tables also show the mean, minimum and maximum continuously compounded returns of the variables. Skewness and kurtosis statistics are also reported, as well as the Jarque-Bera test for normality of the distribution of returns. One asterisk denotes rejection of the null hypothesis of the Jarque-Bera test at 1% significance level. BDI, BCI and BPI are skewed to the left and TD3 is skewed to the right. All Baltic Indices and commodities exceed extreme kurtosis. Largest kurtosis exceeds one-month interbank Libor rate and smallest S&P GSCI Grains index.

Figure 4 shows the evolution of the IMAREX futures series for the four shortest futures maturities for a Basket of four Time-Chartered Capesize routes (CS4TC), the four shortest futures maturities for a Basket of four Time-Chartered Panamax routes (PM4TC) and the four shortest futures maturities for the Dirty Tanker TD3 route. Table 11 reports the summary statistics of the freight futures.

Figure 4

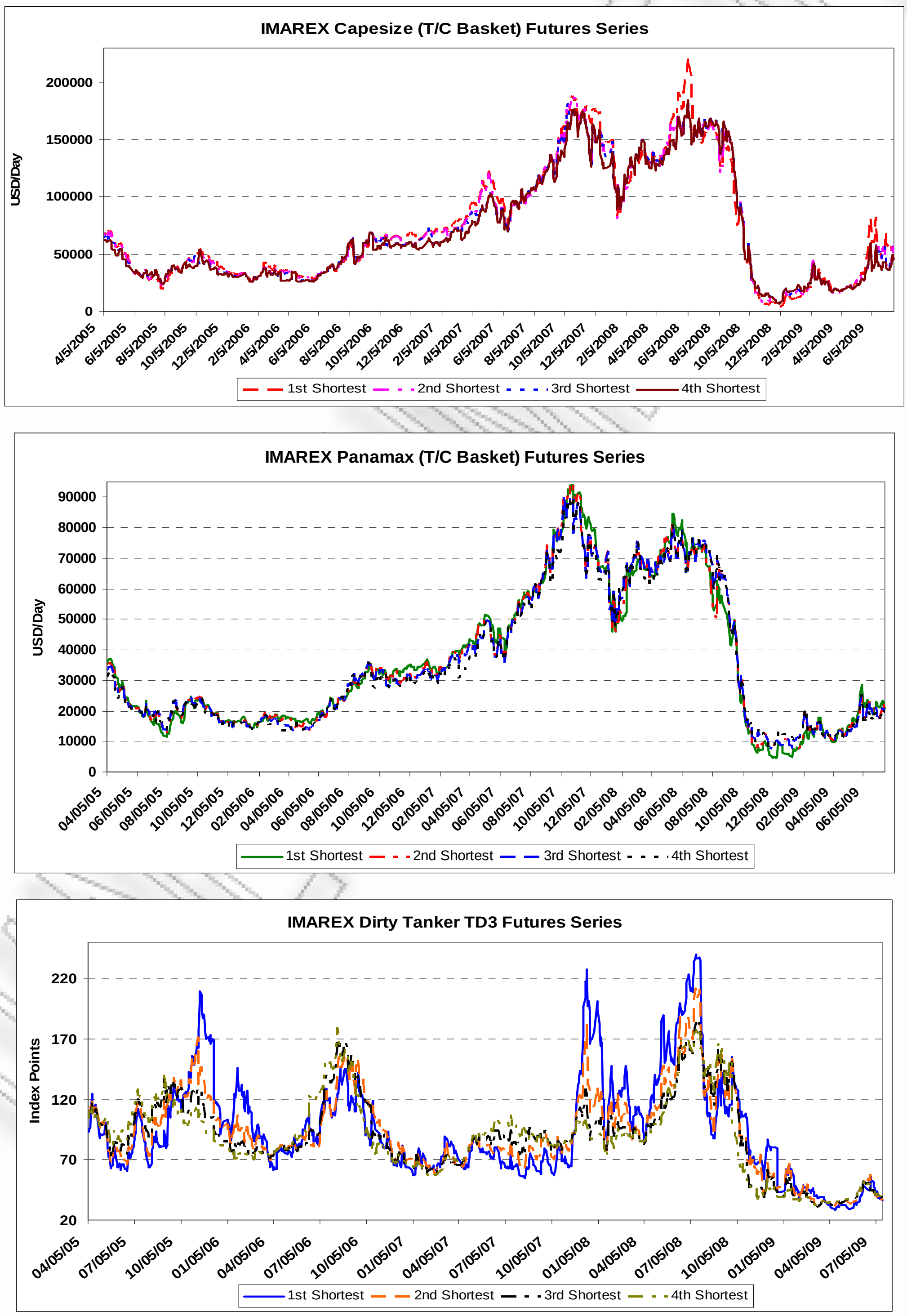


Table 11

Descriptive statistics for Freight Futures

	Levels				Differences			
Panel A: Capesize (T/C Basket) IMAREX Futures on Levels and Differences								
	1st Shortest	**2nd Shortest**	**3rd Shortest**	**4th Shortest**	**1st Shortest**	**2nd Shortest**	**3rd Shortest**	**4th Shortest**
Mean	73924.9	72068.5	71179.3	69835.8	-0.0002	-0.0002	-0.0003	-0.0003
Standard Dev	50501.7	48508.3	48050.3	47554.1	0.06	0.06	0.05	0.05
Minimum	3644	6844	6844	6844	-0.36	-0.36	-0.41	-0.42
Maximum	222125	188010	184719	184719	0.92	0.45	0.24	0.25
Skewness	0.8	0.75	0.77	0.80	2.74	0.45	-0.79	-0.78
Kurtosis	2.54	2.28	2.25	2.28	53.72	12.32	10.16	10.29
Jarque-Bera	**123.89***	**123.88***	**131.65***	**138.18***	**116262.07***	**3919.61***	**2401.13***	**2482.19***
ρ_1	0.997	0.997	0.997	0.997	0.199	0.268	0.310	0.281
ADF	-0.93	-0.97	-0.98	-0.97	**-18.45***	**-19.05***	**-19.60***	**-19.60***
Observations	1073	1073	1073	1073	1072	1072	1072	1072
Panel B: Panamax (T/C Basket) IMAREX Futures on Levels and Differences								
	1st Shortest	**2nd Shortest**	**3rd Shortest**	**4th Shortest**	**1st Shortest**	**2nd Shortest**	**3rd Shortest**	**4th Shortest**
Mean	36097.5	35929.7	35729.3	35277.1	-0.0005	-0.0005	-0.0005	-0.0004
Standard Dev	23141.8	22778.8	22575.7	22295.1	0.05	0.05	0.05	0.05
Minimum	4688	6889	7390	7390	-0.36	-0.21	-0.22	-0.22
Maximum	94110	94110	90225	90225	0.76	0.38	0.33	0.27
Skewness	0.74	0.74	0.73	0.76	3.50	0.78	0.14	-0.15
Kurtosis	2.34	2.28	2.16	2.18	52.88	12.10	8.13	7.34
Jarque-Bera	**116.75***	**121.78***	**127.90***	**133.59***	**113331***	**3811.11***	**1180.56***	**846.71***
ρ_1	0.998	0.997	0.997	0.997	0.125	0.232	0.221	0.226
ADF	-0.82	-0.93	-0.91	-0.89	**-20.64***	**-19.75***	**-21.16***	**-20.56***
Observations	1073	1073	1073	1073	1072	1072	1072	1072
Panel C: Dirty Tanker TD3 IMAREX Futures on Levels and Differences								
	Levels				**Differences**			
	1st Shortest	**2nd Shortest**	**3rd Shortest**	**4th Shortest**	**1st Shortest**	**2nd Shortest**	**3rd Shortest**	**4th Shortest**
Mean	94.97	91.95	90.01	89.24	-0.0009	-0.001	-0.0009	-0.0009
Standard Dev	42.18	34.86	33.02	33.28	0.06	0.05	0.04	0.04
Minimum	28	30.5	31	30.5	-0.61	-0.49	-0.32	-0.43
Maximum	240	212	184	181	0.35	0.31	0.29	0.29
Skewness	1.03	0.59	0.36	0.41	-0.64	-0.65	-0.37	-0.97
Kurtosis	4.05	3.33	2.88	2.95	17.59	13.44	11.91	23.75
Jarque-Bera	**243.43***	**67.74***	**24.30***	**30.59***	**9583.30***	**4942.59***	**3567.55***	**19393.25***
ρ_1	0.987	0.987	0.991	0.993	0.138	0.158	0.115	0.087
ADF	-1.37	-1.32	-1.15	-1.07	**-21.19***	**-20.35***	**-22***	**-22.45***
Observations	1073	1073	1073	1073	1072	1072	1072	1072

Entries report the summary statistics of each one of the Dry Bulk IMAREX Futures on Levels (Panel A) and differences (Panel B) and for the Dirty Tanker TD3 Route (Panel C). The first order autocorrelation ρ_1, the Jarque-Bera and the Augmented Dickey Fuller (ADF) test values are also reported. One and two asterisks denote rejection of the null hypothesis at the 1% and 5% level, respectively. The null hypothesis for the Jarque-Bera and the ADF tests is that the series is normally distributed and has a unit root, respectively. The sample period is from 5 April 2005 to 17 July 2009

Moreover, we apply the Engle ARCH test for heteroskedasticity effects and the Engle and Ng (1993) asymmetric (leverage) tests on the raw spot and futures return series. These asymmetry tests are used as summary statistics to explore the nature of time-varying volatility in the data series, the *sign bias test*, the *negative size bias test*, the *positive size bias test* and the joint test. The sign bias test considers the variable S_{t-1}^{-}, a dummy variable that takes a value of one when data return y_{t-1} is negative and zero otherwise. This test examines the impact of positive and negative return shocks on volatility not predicted by any model. The negative size bias test utilizes the variable $S_{t-1}^{-}y_{t-1}$. It focuses on the different effects that negative return shocks have on volatility. The positive size bias test utilizes the variable $S_{t-1}^{+}y_{t-1}$, where $S_{t-1}^{+}=1-S_{t-1}^{-}$. This test focuses on the positive shocks on volatility. The joint test consists the three variables jointly.

Table 12 reports the results of the ARCH and Engle and Ng tests for the four Baltic Exchange Indices and the IMAREX freight futures. Results point out the use of GARCH and asymmetric volatility models, since we reject the null hypothesis of no heteroskedasticity and no asymmetry effects. In all cases, we accept the null hypothesis for the Sign Bias test. However, Engle and Ng (1993) comment that the power of the sign bias test is weak.

Table 12
Heteroskedasticity and Assymetry tests on data returns

Index	ARCH(1)	ARCH(5)	ARCH(12)	Sign Bias	Negative size bias	Positive size Bias	Joint test for 3 effects
Baltic Dry	557.51*	562.18*	577.74*	1.06	-50.02*	63.04*	618.88*
Baltic Capesize	273.75*	291.71*	303.23*	0.47	-66.07*	44.9*	642.06*
Baltic Panamax	556.37*	557.32*	572.6*	1.13	-82.78*	19.54*	694.37*
Baltic TD3	37.79*	101.5*	108.16*	-0.87	-79.68*	35.6*	364.85*
F_Capesize 1st shortest	0.23	2.69	26.2*	-0.18	-3.83*	122.19*	316.08*
F_Capesize 2nd shortest	14.54*	57.32*	71.57*	1.2	8.08*	20.15*	61.71*
F_Capesize 3rd shortest	39.09*	79.11*	95.78*	1	-38.64*	-1.59	178.27*
F_Capesize 4th shortest	16.96*	42.93*	63.2*	0.49	-29.71*	-7.35*	140.32*
F_Panamax 1st shortest	0.19	0.20	37.66*	-0.23	14.86*	139.37*	320.61*
F_Panamax 2nd shortest	7.64*	41.35*	49.26*	-0.01	-12.72*	58.52*	221.11*
F_Panamax 3rd shortest	28.54*	88.75*	121.72*	1.35	-9.39*	11.54*	92.41*
F_Panamax 4th shortest	24.84*	64.51*	78.08*	1.56	-24.15*	12.86*	129.86*
F_TD3 1st shortest	0.48	1.09	17.05	-0.09	-81.58-	19.48*	217.91*
F_TD3 2nd shortest	0.29	8.13	19.25	-0.46	-39.77*	5.28*	150.62*
F_TD3 3rd shortest	3.64	12.12*	31.3*	0.21	-27.19*	-2.38*	53.21*
F_TD3 4th shortest	0.01	0.96	11.93	-0.2	-3.59*	-48.04*	57.01*

Table reports the results of the Engle ARCH test and the Engle and Ng (1993) assymetry tests for Baltic Exchange Indices and IMAREX Futures. ARCH(lags) is the Engle test for heteroskedasticity. The null of the Engle ARCH test and the Engle and Ng asymmetry tests are of no heteroskedasticity effects and no asymmetries respectively. One asterisk denotes rejection of the null hypothesis at 1% significance level.

Chapter 3

Forecasting models

To identify the models that provide the most accurate short-term forecasts of spot freight rates, four model categories are considered. The economic variables model, the univariate Autoregressive Moving Average model, the GARCH-family models and the Vector Autoregression (VAR) model.

3.1 Economic Variables model

The economic variables model tries to forecast the evolution of spot freight prices using certain economic variables. The economic variables model is constructed in a Beenstock and Vergottis framework, which is an equilibrium demand and supply model. Unique factors that characterize every route like vessel size, cargo type etc., it is essential to develop four different econometric models for every index, due to different demand factors. Their specifications are:

Baltic Dry Index

$$\Delta BDI_t = c_1 + \sum_{i=1}^{p} \phi_i \Delta BDI_{t-i} + a_1 COAL_{t-1} + \alpha_2 IM_{t-1} + \alpha_3 GN_{t-1} + \alpha_4 i_{t-1} + \alpha_5 ys_{t-1} + \varepsilon_{1t} \quad (4)$$

Baltic Capesize Index

$$\Delta BCI_t = c_2 + \sum_{i=1}^{p} \phi_i \Delta BCI_{t-i} + \beta_1 COAL_{t-1} + \beta_2 IM_{t-1} + \beta_3 i_{t-1} + \beta_4 ys_{t-1} + \varepsilon_{2t} \quad (5)$$

Baltic Panamax Index

$$\Delta BPI_t = c_3 + \sum_{i=1}^{p} \phi_i \Delta BPI_{t-i} + \gamma_1 GN_{t-1} + \gamma_2 i_{t-1} + \gamma_3 ys_{t-1} + \varepsilon_{3t} \quad (6)$$

Baltic TD3 Route

$$\Delta TD3_t = c_4 + \sum_{i=1}^{p} \phi_i \Delta TD3_{t-i} + \delta_1 WTI_{t-1} + \delta_2 i_{t-1} + \delta_3 ys_{t-1} + \varepsilon_{4t} \quad (7)$$

where ΔBDI_t is the log-returns of the Baltic Dry Index, ΔBCI_t is the log-returns of the Baltic Capesize Index, ΔBPI_t is the log-returns of the Baltic Panamax Index ,

$\Delta TD3_t$ is the log-returns of the Baltic TD3 Route and c are constants. $COAL$ is the log-returns of Coal spot prices, IM is the log-returns of the industrial metals spot prices, GN is the log-returns of grain spot prices and WTI is the log-returns of the West Texas Intermediate spot crude oil. i is the Libor 1 month interbank rate and ys is the yield curve.

Due to unavailability of a measure or proxy of supply variables, the results are conditioned upon this fact.

In the case of the IMAREX futures series, the regressors of the economic variables remain the same augmented by the returns of the spot indices.

Beenstock and Vergottis (1989a) mention that demand for freight services reflects the volume of seaborne trade which in turn reflects the level and structure of world economic activity both geographically and in terms of the kind of commodities traded. They continue mentioning that in theory demand will vary inversely with freight rates because higher freight rates will create an incentive to use other forms of transportation. However, in practice, such behavior has not been observed. It was unable to discover a negative relationship between demand and freight rates. To conclude, Beenstock and Vergottis (1989a) mention that when a demand shock for commodities is anticipated, it leads to immediate speculative increases in ship prices that also depress scrapping procedures. For the tanker section, Poulakidas and Joutz (2009) use crude oil spot prices and US weekly oil inventories for their econometric model.

3.2 Univariate autoregressive moving average models.

Univariate autoregressive moving average models or Box-Jenkins models are employed in order to examine whether the evolution of the Baltic Exchange indices can be forecasted using its previous values, since daily returns of the Baltic Exchange indices exceed strong autocorrelation. The ARMA (p, q) specification is:

$$\begin{aligned} \Delta y_t &= a_0 + \sum_{i=1}^{p} a_i \Delta y_{t-i} + \sum_{j=1}^{q} b_j \varepsilon_{t-j} + \varepsilon_t \\ \varepsilon_t &\sim IN\left(0, \sigma^2\right) \end{aligned} \tag{8}$$

where Δy_t is the daily returns for each Baltic index and IMAREX futures. The model consists of two parts, an autoregressive (AR) part and a moving average (MA) part. The model is usually then referred to as the ARMA (*p*, *q*) model where *p* is the order of the autoregressive part and *q* is the order of the moving average part. Lags of the ARMA (p, q) models are used after minimizing the Akaike and Scwhartz Information criterions (within a range up to ten lags).

3.3 General autoregressive conditional heteroskedasticity (GARCH) models.

Due to the high heteroskedasticity, asymmetric effects and extreme kurtosis that daily returns of the Baltic indices exhibit, general autoregressive conditional heteroskedastic (GARCH) models are used to catch the error processes effects. We use the GARCH (p, q), the EGARCH (p, q), the GJR-GARCH (p, q) and the GARCH-M (p, q) models for two alternative conditional probability functions of the indices returns: the normal and the Student-t distributions (see Bollerslev (1987)). The latter is used to capture the distributional characteristics of the freight indices that differ from the ones of the normal distributional as described in Angelidis and Skiadopoulos (2008). Extreme kurtosis in Baltic Indices and Imarex futures reported in tables 10-11, support the use of Student-T distribution. Furthermore, Giacomini et al. (2008) describe the usefulness of Student-t distribution in density forecasting and econometrics in general. Angelidis and Skiadopoulos (2008) propose the use of Garch models that capture the potential presence of the leverage effect in the freight indices. In table 12 results of the ARCH and the asymmetries tests pointed out the use of GARCH and asymmetry volatility models. Chen and Wang (2004) concluded that the phenomenon of an asymmetric impact seems to be an inherent nature in freight market, after applying EGARCH model. Leverage effect is the asymmetric negative correlation between volatility and index prices. Engle and Ng (1993) describe this leverage effect thoroughly. Leverage effect occurs when an unexpected drop in prices (bad news) increases volatility more than an unexpected increase in prices (good news) of the same magnitude. Therefore, we use EGARCH and GJR-GARCH models described below. Finally, Engle et al. (1987) conclude that conditional variance can be a significance determinant of the financial returns, suggesting the use of ARCH-In-Mean models.

The GARCH (p, q) model proposed by Bollerslev (1986) is:

$$\begin{aligned}
&\Delta y_t = a_0 + \sum_{i=1}^{p} a_i \Delta y_{t-i} + \sum_{j=1}^{q} b_j \varepsilon_{t-j} + \varepsilon_t \\
&\varepsilon_t \sim distr\left(0, \sigma_t^2\right) \\
&\sigma_t^2 = \omega + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} b_i \sigma_{t-i}^2
\end{aligned} \tag{9}$$

The EGARCH (p, q) model proposed by Nelson (1991) is:

$$\begin{aligned}
&\Delta y_t = a_0 + \sum_{i=1}^{p} a_i \Delta y_{t-i} + \sum_{j=1}^{q} b_j \varepsilon_{t-j} + \varepsilon_t \\
&\varepsilon_t \sim distr\left(0, \sigma_t^2\right) \\
&\log\left(\sigma_t^2\right) = \omega + \sum_{i=1}^{q} \left(a_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right) + \sum_{i=1}^{p} \left(b_i \log\left(\sigma_{t-i}^2\right) \right)
\end{aligned} \tag{10}$$

The GJR-GARCH (p, q) model proposed by Glosten et al. (1993) is:

$$\begin{aligned}
&\Delta y_t = a_0 + \sum_{i=1}^{p} a_i \Delta y_{t-i} + \sum_{j=1}^{q} b_j \varepsilon_{t-j} + \varepsilon_t \\
&\varepsilon_t \sim distr\left(0, \sigma_t^2\right) \\
&\sigma_t^2 = \omega + \sum_{i=1}^{q} \left(a_i \varepsilon_{t-i}^2 + \gamma_i S_{t-i}^{-} \varepsilon_{t-i}^2 \right) + \sum_{i=1}^{p} b_i \sigma_{t-i}^2
\end{aligned} \tag{11}$$

where S_{t-i}^{-} takes the value of 1 when ε_{t-i}^2 is negative and the value of 0 when ε_{t-i}^2 is positive or zero. When the coefficient S_{t-i}^{-} is zero, the model in Eq. (11) is the symmetric GARCH. When $\gamma_i > 0$, the model produces a larger response for a negative shock compared to a positive shock of the same magnitude.

The GARCH-M (p, q) model proposed by Engle et al. (1987) is:

$$\begin{aligned}
&\Delta y_t = a_0 + \sum_{i=1}^{p} a_i \Delta y_{t-i} + \sum_{j=1}^{q} b_j \varepsilon_{t-j} + \beta \sigma_t + \varepsilon_t \\
&\varepsilon_t \sim distr\left(0, \sigma_t^2\right) \\
&\sigma_t^2 = \omega + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} b_i \sigma_{t-i}^2
\end{aligned} \tag{12}$$

3.4 Vector Autoregression (VAR) models

Vector autoregression (VAR) is an econometric model used to capture the evolution and the interdependencies between multiple time series, generalizing the univariate ARMA models. All the variables in a VAR are treated symmetrically by including for each variable an equation explaining its evolution based on its own lags and the lags of all the other variables in the model. There has been a wide use of VAR models in freight literature as described in a recent survey by Glen (2006). The recent focus in modeling freight markets has been on re-examining the statistical properties of shipping market data and then exploring the data set in terms of the existence or otherwise of cointegrating relations between the variables. Since VAR models make no distinction between endogenous and exogenous variables, it is clear that the recent research agenda has shifted away from large econometric models of shipping markets. The VAR (p) specification is:

$$\Delta \boldsymbol{BI}_t = \boldsymbol{C} + \sum_{i=1}^{p} \boldsymbol{a}_i \Delta \boldsymbol{BI}_{t-i} + \boldsymbol{\varepsilon}_t \tag{13}$$

where $\Delta \boldsymbol{BI}_t$ is a (4×1) vector of daily logarithmic differences of the spot prices of the Baltic indices and $\boldsymbol{C}$ is a (4×1) vector of constants. Finally, $\boldsymbol{a}_i$ is a (4×4) matrix of coefficients and $\boldsymbol{\varepsilon}_t$ is a (4×1) vector of residuals. The proper lag P is the one that minimizes the AIC and BIC criterions, tested for up to ten lags.

Chapter 4
Methodology

4.1 In-sample Evidence

In Section 2.5 the results of the unit root tests on the levels and first differences of the daily variables indicate that all variables are first difference stationary. This means that the first differences of daily spot Baltic indices should be used in the all econometric models. We select the proper lags for the specifications of the models, estimate their coefficients and present their in-sample performance.

The selection criteria for the appropriate lag length are used to avoid overparameterizing the models and produce parsimonious ones. The Bayesian Schwartz Information criterion (BIC) and the Akaike Information Criterions (AIC) are used widely in the literature. They derive as follows:

$$AIC = (-2 * LLF) + (2 * c) \quad (14)$$

$$BIC = (-2 * LLF) + (2 * c * T) \quad (15)$$

LLF is the optimized loglikelihood objective function associated with the parameter estimation of the models. c is the number of parameters and T is the number of observations.

In order to evaluate the significance of the coefficients, we use a hetetoskedasticity and autocorrelation consistent covariance matrix proposed by Newey and West (1987) to calculate the coefficients' standard errors. For the estimation of the covariance matrix, Andrews (1991) suggested using a quadratic spectral lag window together with a "plug-in" automatic bandwidth selection procedure. However, a Bartlett's kernel was employed and the required lag selection parameter was set equal to $\left[4(T/100)^{2/9}\right]$, as been proposed by Newey and West (1994), where T is the number of observations.

Therefore, Newey-West t-statistics are reported in parenthesis and one or two asterisks denote rejection of the null hypothesis of a zero coefficient at 1% and 5% significance level. Finally, tables in next sections show the Akaike and the Bayesian Information Criterions and the adjusted R^2 for each one of the Baltic indices.

4.2 Out-of-sample Evidence: Statistical significance

In order to assess the out-of-sample performance of the models described in Section 4, we produce point and interval forecasts of the four Baltic exchange indices. We produce out-of sample forecasts for one step ahead over the period 5 April 2005 to 17 July 2009. To perform a comprehensive comparison of the forecasting performance of the Baltic indices, we consider all alternative models of predicting spot returns as described in Section 3. Furthermore, the random-walk (RW) model is also considered for benchmark comparison for point forecasts. Random-walk model considers that today spot prices (y_t) are the most accurate predictors of spot prices over one step ahead (y_{t+1}).

We form point forecasts by applying the methodology of the "rolling window" (see Pesaran and Timmermann (2003)). Due to the coefficient instability over the whole sample period, we will use an observation window for our forecasts. In the asset pricing literature is believed that if parameters of the regression model are not believed to be constant over, a "rolling" window of observations with a fixed size is used to generate forecasts. Since our sample period (2005 to 2009) is large and contains one business cycle, we believe that parameters are not constant over time. Therefore, the models are initially estimated over the in-sample period (from 5 April 2005 to 29 September 2006) and the first out-of-sample forecasts are obtained. The remaining out-of-sample forecasts are constructed by re-estimating the models recursively by adding one observation to the data set and removing the first observation, thus maintaining a "rolling" window of 375 observations and constructing 697 out-of-sample forecasts.

The bootstrapped interval forecasts are constructed by applying the methodology suggested by Pascual et al. (2001) for ARMA, VAR and economic variables models and Monte Carlo simulation for the GARCH models. One each time step (day) 10.000 bootstrap samples and 10.000 simulation runs are formed, in order to construct 95% prediction intervals.

We now describe the bootstrap procedure suggested by Pascual et al. (2001) to construct interval forecasts. We have an ARMA process as in equation (8).

<u>*Step 1*</u>

From an observed series, the parameters can be estimated by a consistent estimator. Given these parameters, residuals are calculated from the equation below:

$$\boldsymbol{\varepsilon}_t = \Delta \boldsymbol{y}_t - \boldsymbol{a}_0 - \sum_{i=1}^{p} \boldsymbol{a}_i \Delta \boldsymbol{y}_{t-i} - \sum_{j=1}^{q} \boldsymbol{b}_j \boldsymbol{\varepsilon}_{t-j} \tag{16}$$

Derive the centered residuals and denote by $\hat{F}_\varepsilon$ their empirical distribution. Centered residuals are derived by the following equation:

$$\hat{\boldsymbol{\varepsilon}}_t = \boldsymbol{\varepsilon}_t - \frac{1}{\boldsymbol{T}-1} \sum_{j=1}^{t-1} \boldsymbol{\varepsilon}_j \tag{17}$$

The reason for using centered residuals in the next step (resampling residuals) is described in Paparoditis and Politis (2003). Although residuals have zero mean, the estimated residuals after the resampling process will have nonzero mean. This discrepancy has an important effect on the bootstrap distribution effectively leading to a random walk with drift in the bootstrap world.

Step 2

We generate a bootstrap replicate of the series $\{y_1^*, \ldots, y_T^*\}$ by the following equation:

$$\Delta \boldsymbol{y}_t^* = \boldsymbol{a}_0 + \sum_{i=1}^{p} \boldsymbol{a}_i \Delta \boldsymbol{y}_{t-i}^* + \sum_{j=1}^{q} \boldsymbol{b}_j \hat{\boldsymbol{\varepsilon}}_{t-j}^* + \hat{\boldsymbol{\varepsilon}}_t^* \tag{18}$$

where $\hat{\boldsymbol{\varepsilon}}_{\boldsymbol{T}}^*$ are random draws from $\hat{F}_\varepsilon$. Next, we estimate the parameters of the bootstrap series, say $\{\alpha_0^*, \alpha_1^*, \ldots, \alpha_p^*, b_1^*, b_2^*, \ldots, b_q^*\}$ and proceed in the next step.

Step 3

Obtain a bootstrap future value for the transformed series for 1 step ahead as follows:

$$\Delta \boldsymbol{y}_{T+1}^* = \boldsymbol{a}_0^* + \sum_{i=1}^{p} \boldsymbol{a}_i^* \Delta \boldsymbol{y}_{T-i}^* + \sum_{j=1}^{q} \boldsymbol{b}_j^* \hat{\boldsymbol{\varepsilon}}_{T-j}^* + \hat{\boldsymbol{\varepsilon}}_T^* \tag{19}$$

Step 4

Repeat the last three steps *B* times to obtain a set of *B* bootstrap replicates for $\boldsymbol{y}_{T+1}^*$. Then proceed to step 5.

Step 5

The prediction bounds are defined as quantiles of the bootstrap distribution function of y^*_{T+1}. A (100-a) % prediction interval is given by the following equation:

$$\left[L^*_B, U^*_B\right] = \left[Q^*_B\left(\frac{1-a}{2}\right), Q^*_B\left(\frac{1+a}{2}\right)\right] \tag{20}$$

,where L^*_B and U^*_B denote the lower and upper bound of the bootstrapped interval forecast.

4.2.1 Point Forecasts: Statistical Testing.

In order to evaluate the out-of-sample performance of the point forecasts for the period under consideration, we compute three alternative metrics for each model. These metrics have been used for assessing out-of-sample performance by a considerable amount of studies in different commodity and financial markets. Just a few examples of these studies are: Pesaran and Timmermann (1994) in stock market, Kavussanos and Nomikos (2003) in freight futures market, Cheung et al. (2005) in exchange rates, Sadorsky (2006) in energy markets, Gonzales and Guidolin (2006) in options implied volatility, Konstantinidi et al. (2008) in volatility markets (VIX).

The three metrics are described below:

i) The first metric is the Mean Absolute Error (MAE) calculated as the average of the absolute differences between the model's forecast returns and the actual Baltic Indices returns.

$$MAE = \frac{1}{T}\sum_{t=1}^{T}\left(\left|\hat{y}_t - y_t\right|\right) \tag{21}$$

where $\hat{y}_t$ is the model's point forecasts.

ii) The second metric is the Root Mean Square Error (RMSE) calculated as the square root of the average squared deviations of the model's forecast returns from the actual Baltic Indices returns.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{T}\left(\hat{y}_t - y_t\right)^2}{T}} \tag{22}$$

where $\hat{y}_t$ is the model's point forecasts.

iii) The third metric is the Mean Correct Prediction (MCP) computed as the number of correct predictions of the direction of change over the total number of predictions. The metric was developed by Pesaran and Timmermann (1992). The indicator variable takes a value of 1 or 0 according to the predicted sign of the freight rates forecasts.

$$I_t = 1, \hat{y}_t y_t > 0 \tag{23}$$

$$= 0, \text{otherwise.}$$

A value above (below) 50% indicates a better (worse) forecasting performance than a naive model. For trading purposes, information regarding the significance of correct prediction can be used to derive a potentially trading rule. Sometimes, profitable trading strategies result from successful forecasting of market direction, rather than the forecasting returns themselves. Christoffersen and Diebold (2006) summarize the literature on asset return sign forecasting that provide evidence of successful trading. Diebold and Mariano (1995) provide a test statistic for the MCP, $S = \sum_{t=1}^{T} I_t$. Significance of this test statistic may be assessed using a table of the cumulative binomial distribution. In large samples, the studentized version of the sign test statistic is standard normal:

$$S_a = \frac{S - \frac{T}{2}}{\sqrt{\frac{T}{4}}} \sim N(0,1) \tag{24}$$

The null hypothesis is that the model has no equal performance compared to a random walk model. However, due to the fact that MCP cannot be computed for the random walk model, we consider an equal probability the predicted change to be positive or negative. Therefore, the MCP of the random walk is equal to 50%. We used two alternative hypothesis, $H_1 : MCP < 50\%$ and $H_2 : MCP > 50\%$.

After computing the MAE and the RMSE of the models, we perform pairwise comparisons based on the Modified Diebold-Mariano test, as proposed by Harvey et al. (1997)., in order to point out the best performing models. The Modified Diebold-Mariano test is described below. Consider two forecasts $\{\hat{y}_{it}\}_{t=1}^{T}$ and $\{\hat{y}_{jt}\}_{t=1}^{T}$ generated by the model specifications in this dissertation. Furthermore, T denotes the futures maturities (T=1, 2, 3, 4). Let $\left\{e_{t,T}^{i}\right\}_{t=1}^{T}$ and $\left\{e_{t,T}^{j}\right\}_{t=1}^{T}$ be the respective forecast errors for each of the model specifications. Next, we define a loss function $g\left(e_{t,T}^{i}\right)$ and $g\left(e_{t,T}^{j}\right)$ under the Mean Absolute Error and the Root Mean Square Error. The null hypothesis of equal forecast accuracy is $H_0 : E\left(d_{t,T}\right)=0$, where $d_{t,T}=\left[g\left(e_{t,T}^{i}\right)-g\left(e_{t,T}^{j}\right)\right]$ is the loss differential. We test the null hypothesis against two alternative hypotheses. The first alternative hypothesis is that the benchmark model outperforms the respective model, $H_1 : E\left(d_{t,T}\right)>0$. The second alternative hypothesis is that the chosen model outperforms the benchmark model, $H_2 : E\left(d_{t,T}\right)<0$.

In order to take the Modified Diebold-Mariano pairwise comparison results, we need to obtain the MDM test statistic. The test is natural to be based on the sample mean of the loss differential:

$$\bar{d}_T=\frac{\sum_{t=1}^{T} d_{t,T}}{T} \tag{25}$$

The Diebold –Mariano test statistic is:

$$DM_T=\left[V\left(\bar{d}_T\right)\right]^{1/2}\bar{d}_T \tag{26}$$

where $V\left(\bar{d}_T\right)=T^{-1}\left[\gamma_0+2\sum_{k=1}^{h-1}\gamma_k\right]$ is the variance of $\bar{d}_T$ and the kth autocovariance of d_t is $\hat{\gamma}_k=T^{-1}\sum_{t=k+1}^{T}\left(d_t-\bar{d}_T\right)\left(d_{t-k}-\bar{d}_T\right)$. A Bartlett's kernel was employed and the required lag selection parameter was set equal to $\left[4\left(T/100\right)^{2/9}\right]$, as been proposed by Newey and West (1994), where T is the number of observations. The Modified Diebold-Mariano test statistic is:

$$MDM_T=\left[\frac{T+1-2h+T^{-1}h(h-1)}{T}\right]^{1/2} DM_T, \tag{27}$$

where h is the forecast horizon. Finally, we accept or reject the null hypothesis by comparing the MDM statistic with critical values from the Student's T distribution with $(T-1)$ degrees of freedom.

4.2.2 Interval Forecasts: Statistical Testing.

In order to assess the out-of-sample performance of the constructed interval forecasts for the period under consideration, the likelihood test of unconditional coverage of Christoffersen (1998) has been used. The following procedure describes the unconditional coverage likelihood test of Christoffersen (1998).

Consider the sample path of each one of the Baltic Indices and IMAREX futures $\{BI_{t,T}\}_{t=1}^{T}$ and their respective series of interval forecasts $\{L^i_{t/t-1,T}(1-a), U^i_{t/t-1,T}(1-a)\}_{t=1}^{T}$,as described in Section 4. $L^i_{t/t-1,T}(1-a)$ and $U^i_{t/t-1,T}(1-a)$ denote the lower and upper bound of a (1-a)% prediction interval at time *t*, constructed at time *t-1*, for each for the *i*-th model specification. The scope of the statistic is to test whether the percentage of times that the realized Baltic index violates the constructed interval is *a*%. Consequently, an indicator variable takes a value of 1 or 0 according to the violations of the prediction intervals:

$$I^i_{t,T} = \begin{cases} 0, \text{ if } \mathrm{BI}_{t,T} \in \left[L^i_{t/t-1,T}(1-a), U^i_{t/t-1,T}(1-a)\right] \\ 1, \text{ if } \mathrm{BI}_{t,T} \notin \left[L^i_{t/t-1,T}(1-a), U^i_{t/t-1,T}(1-a)\right] \end{cases} \tag{28}$$

The value of the likelihood ratio LR_{unc} is given by the following equation:

$$LR_{unc} = 2\ln\left[\left(1-\frac{N}{T}\right)^{T-N}\left(\frac{N}{T}\right)^{N}\right] - 2\ln\left[(1-p)^{T-N} p^{N}\right] \sim \chi^2(1) \tag{29}$$

where N is the number of times that a violation has occurred. The test statistic follows a chi-square distribution with one degree of freedom. However, the power of this test may be sensitive to the sample size. Therefore, we generate Monte Carlo simulated p-values in order to assess the statistical significance of the test statistic, as proposed in Christoffersen (2003).

The steps to calculate the Monte Carlo simulated p-values are described below. Firstly, a sample of *T* iid Bernoulli(*a*) variables is simulated. Secondly, Christoffersen's test statistic is obtained for the simulated sample. Next, this procedure is repeated K=9,999 times and the empirical distribution of Christoffersen's test statistic is obtained under *a%* significance level. Let M be the number of times that the observed test statistic is more extreme than the simulated ones. Finally, the Monte-Carlo *p*-value equals $(1+M)/(1+K)$. Therefore, the null hypothesis of an efficient (1-a)% interval forecast is $H_0 : E\left(I_{t,T}^{i}\right) = a$ and the alternative hypothesis is $H_1 : E\left(I_{t,T}^{i}\right) \neq a$.

4.3 Out-of-sample Evidence: Economic significance.

In order to provide a firm answer on the question of predictability in freight markets, we investigate the economic significance of the obtained forecasts. We assess the economic significance by performing trading strategies based on point and interval forecasts. The trading strategies involve a single freight futures contract throughout the trading period. Transaction costs have been taken into account to make our trading strategies more realistic. Trading costs have been referred in chapter 2.4.

4.3.1 Economic significance: Performance Measures

In order to evaluate the out-of-sample economic significance of the point and interval forecasts for the period under consideration, we compute two alternative metrics for each model: Sharpe Ratio (SR) and Leland's alpha (A_p), as proposed by Leland (1999). Due to the non-normality of the strategy returns, the usual asymptotic standard errors are not suitable for the statistical significance of the metrics. We base our tests on the empirical distribution from 1000 bootstrap repetitions of our sample. The statistical significance of the two performance measures is assessed by bootstrapping their 95% confidence intervals. For the bootstrap process we have employed the stationary bootstrap by Politis and Romano (1994)[3]. In order to construct the bootstrap time series, the stationary bootstrap resamples blocks of random size from the original time series. This block size follows a geometric distribution with mean block length 1/q. We let the block size be chosen by the processes described by Politis and White (2004) and Patton et al. (2009). The authors

[3] The stationary bootstrap is applicable to stationary and weakly dependent time series. Returns of the trading strategies have been found to be stationary.

provide the optimal block size for the stationary bootstrap. The optimal block size choice is given by:

$$\hat{b}_{opt} = \left(\frac{2\hat{G}^2}{\hat{D}_{SB}} \right)^{1/3} T^{1/3} \tag{30}$$

where $\hat{G}$ and $\hat{D}_{SB}$ are estimators.

We use the continuously compounded one month Libor rate as the risk free to calculate the measures of performance.

Sharpe's Ratio is calculated by the following equation:

$$SR_p = \left[E\left(r_p\right) - r_f \right] / \sigma_p \tag{31}$$

In order to account for the presence of non-normality in the distribution of the trading strategies' returns we use Leland's (1999) alpha. Leland's alpha is calculated by the following equation:

$$A_p = E\left(r_p\right) - B_p \left[E\left(r_m\right) - r_f \right] - r_f \tag{32}$$

where r_p is the return of the trading strategy, r_m is the of the market portfolio, r_f is the risk-free rate, $B_p = \dfrac{\operatorname{cov}\left(r_p, -\left(1+r_m\right)^{-\gamma}\right)}{\operatorname{cov}\left(r_m, -\left(1+r_m\right)^{-\gamma}\right)}$ and $\gamma = \dfrac{\ln\left[E\left(1+r_m\right)\right] - \ln\left(1+r_f\right)}{\operatorname{var}\left[\ln\left(1+r_m\right)\right]}$. B_p is the measure of risk similar to the CAPM's beta and γ is the coefficient of "market price of risk" : the market's instantaneous excess rate of return divided by the variance of the market's instantaneous rate of return. As proxies for the market returns and the risk-free rate, we use the returns on the FTSE Maritime index and the one month Libor rate respectively.

If $A_p > 0$ we conclude that the trading strategy offers an expected excess return of its risk adjusted level.

4.3.2 Trading Strategy based on Point Forecasts

The following trading rule is employed in order to assess the economic significance of the constructed point forecasts.

If $Y_T < (>) \hat{Y}_{T+1}$, then go long (short).

If $Y_T = \hat{Y}_{T+1}$, then do nothing.

where Y_T are the Baltic Exchange Indices and the IMAREX freight futures.

If the forecasted value of the index of interest is higher (lower) than the actual value, the index is expected to increase (decrease). Therefore, the investor takes a long (short) position on the IMAREX futures.

4.3.3 Trading Strategy based on Interval Forecasts

The following trading rule is employed in order to assess the economic significance of the constructed interval forecasts.

If $Y_T < (>) \dfrac{\hat{U}_{T+1}(1-\alpha)+\hat{L}_{T+1}(1-\alpha)}{2}$, then go long (short).

If $Y_T = \dfrac{\hat{U}_{T+1}(1-\alpha)+\hat{L}_{T+1}(1-\alpha)}{2}$, then do nothing.

where Y_T are the Baltic Exchange Indices and the IMAREX freight futures.

If the actual value of the index of interest is closer to the lower (upper) bound of the forecasted intervals, the index is expected to increase (decrease). Therefore, the investor takes a long (short) position on the IMAREX futures.

Chapter 5

Spot Freight Rates: Results and Discussion

5.1 In-Sample Evidence

Tables 13 – 15 show present the in-sample performance of the economic variables, ARMA, VAR and GARCH-family models and the estimated coefficients.

Table 13 reports the in-sample performance of the economic variables model. The set of the economic variables was augmented with lagged terms of the Baltic indices, chosen by the BIC criterion. The table shows the coefficients of the regression, the AIC and BIC values and the adjusted R^2. The R^2 takes the largest value for the Baltic Dry Index (78.49%). This is similar to the values of adjusted R^2 documented by previous related literature; for instance, see Jonnala et al. (2002), Kavussanos and Nomikos (2003) and Batchelor et al. (2007).

Table 13

Forecasting Baltic Exchange Indices with the Economic Variables model

	Baltic Dry Index	**Baltic Capesize Index**	**Baltic Panamax Index**	**TD3 Route**
c	0.0004	0.0002	0.0006	0.0013
	(1.108)	(0.366)	(1.263)	(0.627)
AR(1)	**1.193***	**1.046***	**1.251***	**0.66***
	(15.08)	(13.805)	(27.836)	(19.444)
AR(2)	**-0.396***	**-0.306***	**-0.488***	-
	(-5.292)	(-4.761)	(-8.559)	
$Coal_{t-1}$	0.0002	0.0005	-	-
	(1.405)	(1.068)		
IM_{t-1}	-0.0003	**-0.0007***	-	-
	(-1.798)	(-2.594)		
GN_{t-1}	0.00001	-	-0.0002	-
	(-0.28)		(-0.599)	
WTI_{t-1}	-	-	-	-0.0005
				(-0.54)
i_{t-1}	-0.0008	0.0011	-0.0017	-0.0114
	(-0.639)	(0.472)	(-0.703)	(-1.495)
ys_{t-1}	-0.0013	-0.0016	-0.0018	0.0025
	(0.684)	(-1.27)	(-1.452)	(0.757)
AIC	-2644.35	-2252.65	-2442.23	-1495.16
BIC	-2609.01	-2221.24	-2414.74	-1471.60
Adj. R^2	0.7849	0.6892	0.7804	0.4317

The entries report results from the estimation of the economic variables models for the daily changes of the Baltic Exchange Indices. AR: a lagged term of each Baltic index, c: a constant, Coal: the log-return of coal prices, IM: log-returns of the S&P GSCI Industrial Metals index, GN: the log-returns of the S&P GSCI Grain Index, WTI: the log-returns of the WTI Crude oil, i: the one month Libor rate in log-differences, ys: the slope of the yield curve calculated as the difference between the prices of the ten year U.S. government bond and the one-month interbank rate. The estimated coefficients, Newey-West t-statistics in parenthesis, the Akaike and Bayesian information criterion and the adjusted R^2 are reported. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% level. The models have been estimated for the period 5 April 2005 to 29 September 2006.

Table 14

Forecasting Baltic Indices with ARMA, VAR and GARCH models

	Baltic Dry	**Baltic Capesize**	**Baltic Panamax**	**TD3**
Panel A:	**AR(2)**	**AR(2)**	**AR(2)**	**AR(1)**
c	-0.0006	-0.0002	-0.0005	0.0001
	(-0.167)	(-0.385)	(-0.095)	(0.068)
AR(1)	**1.203***	**1.084***	**1.253***	**0.661***
	(16.147)	(14.575)	(27.669)	(19.438)
AR(2)	**-0.391***	**-0.336***	**-0.478***	-
	(-5.434)	(-5.291)	(-8.647)	
AIC	-2647.52	-2253.60	-2442.67	-1498.20
BIC	-2631.82	-2237.89	-2426.96	-1486.42
Adj. R^2	0.7839	0.6867	0.7790	0.4318

Panel B: VAR(1)				
c	-0.0001	-0.0001	-0.0002	0.0001
	(-0.18)	(-0.158)	(-0.036)	(0.056)
ΔBDI_{t-1}	0.282	-0.12	**-0.474****	-0.214
	(1.74)	(-0.486)	(-1.866)	(-0.514)
ΔBCI_{t-1}	**0.266***	**0.842***	**0.281****	0.188
	(3.5)	(7.513)	(2.367)	(0.955)
ΔBPI_{t-1}	**0.242***	0.091	**0.994***	-0.024
	(3.997)	(0.904)	(9.957)	(-0.147)
$\Delta TD3_{t-1}$	0.012	0.026	0.01	**0.656***
	(0.9)	(1.126)	(0.77)	(18.926)
AIC	-2579.10	-2216.6	-2350.48	-1490.74
BIC	-2598.74	-2196.96	-2330.84	-1471.1
Adj. R^2	0.7595	0.6587	0.7224	0.4311

Panel C: AR / GARCH(1,1)								
	N	**T**	**N**	**T**	**N**	**T**	**N**	**T**
c	-0.0002	-0.0001	-0.0002	-0.0002	0.0001	-0.0001	0.0008	-0.002
	(-0.608)	(-0.487)	(-0.049)	(-0.435)	(0.179)	(-0.22)	(0.484)	(-1.15)
AR(1)	**1.251***	**1.252***	**1.073***	**1.069***	**1.284***	**1.262***	**0.675***	**0.623***
	(16.558)	(16.222)	(15.513)	(15.013)	(28.709)	(28.014)	(20.037)	(17.449)
AR(2)	**-0.391***	**-0.421***	**-0.262***	**-0.293***	**-0.475***	**-0.468***	-	-
	(-5.394)	(-5.776)	(-4.215)	(-4.703)	(-8.491)	(-8.491)		
AIC	-2693.20	-2700.09	-2297.48	-2314.03	-2478.18	-2483.67	-1527.08	-1584.71
BIC	-2669.64	-2672.60	-2273.92	-2286.54	-2454.62	-2456.18	-1507.44	-1561.14
Adj. R^2	0.7803	0.7813	0.6819	0.6837	0.7766	0.7769	0.4283	0.4231

The entries report results from the estimation of the univariate ARMA, ARMA with GARCH error process and VAR model specifications for the daily changes of each Baltic Index. The estimated coefficients, Newey-West t-statistics in parenthesis, the Akaike and Bayesian information criterion and the adjusted R2 are reported. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% level. The models have been estimated for the period 5 April 2005 to 29 September 2006.

Table 14 presents the in-sample performance for the univariate ARMA models, VAR models and the ARMA models with GARCH error processes for two probability functions. The lag length for the autoregressive and moving average parts are chosen to minimize BIC criterion. Therefore, for the Baltic Dry Index, the Baltic Capesize and the Baltic Panamax, the proper model chosen is AR(2) and for the TD3 the AR(1). Furtheromore, AIC and BIC criterions choose VAR (1) as the best fitted model. We observe that all models seem to be well specified, with high coefficients of determination. The highest R^2 is referred in BDI with a 78.39% value.

Table 15 reports the in-sample performance for the univariate ARMA models with EGARCH and GJR error processes and GARCH-In-Mean models. For our model selection, we choose the lag length that minimizes BIC criterion. These four GARCH-family models are estimated for two alternative conditional probability density functions of the indices returns: Normal distribution and the Student-t distribution. For some indices, these specifications could not be estimated. These models seem to be well fitted producing again high adjusted R^2. Moreover, AIC and BIC statistics are smaller compared to the previous models. Again the largest value of R^2 is obtained for the BDI.

High values of the coefficient of determination indicate that there is a predictable pattern for the Baltic Indices. These results are consistent with former literature, as referred before.

To sum up, the in-sample goodness-of-fit statistics provide evidence of predictable patterns for all model specifications and all Baltic indices. We can note that the bigger R^2 is, the bigger is the predictability of spot returns using information from lagged spot prices and economic variables. The observed high adjusted R^2 values of the models may be attributed to the high first order autocorrelations of the freight rates returns (Table 10). Next, the out-of-sample performance is assessed, in order to provide a clear answer on the predictability of the freight rates.

Table 15

Forecasting Baltic Indices with EGARCH, GJR and GARCH-In-Mean models

	Baltic Dry		Baltic Capesize		Baltic Panamax		TD3	
Panel D: AR / EGARCH(1,1)								
	N	**T**	**N**	**T**	**N**	**T**	**N**	**T**
c	-0.0002	-0.0001	0.005	-0.0001	-0.004	-0.0001	0.001	-0.002
	(-0.608)	(-0.36)	(0.091)	(-0.152)	(-0.093)	(-0.32	(0.599)	(-1)
AR(1)	**1.251***	**1.258***	**1.096***	**1.082***	**1.29***	**1.262***	**0.643***	**0.627***
	(16.558)	(16.256)	(15.211)	(14.897)	(28.912	(28.217)	(18.596)	(17.682)
AR(2)	**-0.391***	**-0.424***	**-0.299***	**-0.313***	**-0.491***	**-0.483***	-	-
	(-5.394)	(-5.797)	(-4.774)	(-4.98)	(-9.1)	(-8.82)		
AIC	-2692.27	-2698.70	-2298.95	-2314.03	-2482.29	-2486.29	-1524.42	-1584.49
BIC	-2664.78	-2667.28	-2271.46	-2286.54	-2454.80	-2454.87	-1500.86	-1557.00
Adj. R^2	0.7799	0.7805	0.6822	0.6837	0.7764	0.7764	0.4264	0.4224
Panel E: AR / GJR(1,1)								
	N	**T**	**N**	**T**	**N**	**T**	**N**	**T**
c	-0.0001	-0.0001	-	-0.0002	-0.0001	-0.0002	-	-
	(-0.511)	(-0.487)		(-0.443)	(-0.146)	(-0.457)		
AR(1)	**1.248***	**1.252***	-	**1.069***	**1.288***	**1.263***	-	-
	(16.589)	(16.222)		(15.012)	(28.855)	(28.086)		
AR(2)	**-0.388***	**-0.421***	-	**-0.294***	**-0.478***	**-0.471***	-	-
	(-5.355)	(-5.776)		(-4.705)	(-8.814)	(-8.534)		
AIC	-2691.35	-2698.09	-	-2310.03	-2478.11	-2483.43	-	-
BIC	-2663.86	-2666.67	-	-2274.69	-2450.62	-2452.01	-	-
Adj. R^2	0.7797	0.7807	-	0.6820	0.7759	0.7762	-	-
Panel G: AR / GARCH-In-Mean(1,1)								
	N	**T**	**N**	**T**	**N**	**T**	**N**	**T**
c	**-0.0007****	**-0.0006****	**-0.0012****	**-0.0014****	-0.0006	**-0.0008****	**0.005***	-0.003
	(-2.08)	(-1.996	(-2.183)	(-2.477)	(-1.504)	(-0.22)	(0.484)	(-1.878)
AR(1)	**1.243***	**1.251***	**1.05***	**1.059***	**1.29***	**1.271***	**0.673***	**0.618***
	(17.925)	(16.222)	(18.687)	(17.662)	(28.328)	(28.014)	(20.037)	(17.736)
AR(2)	**-0.38***	**-0.417***	**-0.232***	**-0.282***	**-0.48***	**-0.475***	-	-
	(-5.445)	(-5.776)	(-3.771)	(-4.7)	(-8.84)	(-8.491)		
InMean	10	10	10	10	10	10	-4.517	1.0076
	(0.604)	(0.463)	(0.993)	(1.043)	(0.781)	(0.818)	(-1.066)	(0.748)
AIC	-2691.40	-2697.40	-2298.10	-2314.80	-2476.70	-2482.10	-1521.50	-1581
BIC	-2663.90	-2666.00	-2270.70	-2283.40	-2449.20	-2450.70	-1490.10	-1549.50
Adj. R^2	0.7844	0.7847	0.6896	0.6927	0.7773	0.7777	0.4220	0.4232

The entries report results from the estimation of the univariate ARMA with EGARCH and GJR error process and GARCH-In-Mean model specifications for the daily changes of each Baltic Index. The estimated coefficients, Newey-West t-statistics in parenthesis, the Akaike and Bayesian information criterion and the adjusted R^2 are reported. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% level. The models have been estimated for the period 5 April 2005 to 29 September 2006.

5.2 Out-of-sample Evidence: Statistical Testing

Considering all these points, we construct point and 95% bootstrapped interval forecasts following the procedures described above and perform the three metrics for point forecasts and the likelihood ratio for the interval forecasts. Tables 16 and 17 show the results for each one of the Baltic Exchange Indices. Table 16 shows the MAE, RMSE and MCP obtained for point forecasts based on the models previously described for the Baltic Dry Index (Panel A), the Baltic Capesize Index (Panel B), the Baltic Panamax Index (Panel C) and the Baltic Dirty Route TD3 (Panel D).

In order to compare the forecasting ability of the models, we perform pairwise comparisons using the Modified Diebold-Mariano test, in order to point out the best performing models. Results are reported in Table 18. One and two asterisks (crosses) denote rejection of the null hypothesis in favor of the alternative H_1 (H_2) at 1% and 5% significance level respectively. The null hypothesis is of equal forecasting accuracy between the chosen model and the benchmark. Two alternative hypothesis H_1 and H_2 are considered. H_1: the benchmark model outperforms the chosen model and H_2: the chosen model outperforms the benchmark. The models in "rows" are the chosen models and the models in "columns" are the benchmark models.

It is easy to observe that in 79 cases over 82 possible combinations of Baltic indices and predictability metrics in which one of the models outperform the random walk model (96.34% of cases). The same results occur under the MCP metric in all cases.

In the case of the Baltic Dry Index, the second worst performing model is the VAR(1) and the third worst performing model is the Economic Variables under both metrics. Under both metrics, the null hypothesis of equal performance between the AR(2) and all GARCH-type models cannot be rejected. In the case of the Baltic Capesize Index, the second worst performing model is again VAR(1) and AR(1) under MAE metric. Under the RMSE metric the second worst is only the VAR(1) model. Among the rest models, there is no outperforming model under both metrics. Similarly, in the case of the Baltic Panamax Index the worst performing models are the VAR(1) and the Economic Variables under both metrics. For the rest of the models, there is no outperforming model under both metrics. In the case of the Dirty Tanker TD3 route, the best model is the AR(1)/EGARCH(1,1) - T under the MAE measure outperforming all models. However, under the RMSE metric there is no outperforming model.

Table 16

Out-of-sample performance for each one of the Baltic Exchange Indices

	BDI	BCI	BPI	TD3
A. Random Walk				
MAE	0.980	1.610	1.275	2.789
RMSE	1.493	2.522	2.012	4.627
B. Economic Variables				
MAE	0.891	1.432	1.162	2.461
RMSE	1.390	2.337	1.836	4.162
MCP	86.80%	85.80%	85.94%	78.48%
C. AR				
MAE	0.859	1.522	1.132	2.453
RMSE	1.355	2.390	1.810	4.162
MCP	86.94%	80.92%	86.66%	78.91%
D. VAR				
MAE	0.946	1.538	1.207	2.474
RMSE	1.462	2.414	1.913	4.170
MCP	84.94%	81.64%	85.08%	77.47%
E. AR / GARCH(1,1) - N				
MAE	0.859	1.409	1.125	2.486
RMSE	1.350	2.295	1.776	4.231
MCP	87.52%	87.09%	86.66%	78.91%
F. AR / GARCH(1,1) - T				
MAE	0.856	1.408	1.127	2.418
RMSE	1.347	2.301	1.776	4.131
MCP	88.09%	87.09%	86.51%	79.77%
G. AR / EGARCH(1,1) - N				
MAE	0.865	1.414	1.124	2.456
RMSE	1.364	2.306	1.777	4.187
MCP	87.52%	87.09%	86.66%	79.48%
H. AR / EGARCH(1,1) - T				
MAE	0.861	1.404	1.128	2.409
RMSE	1.353	2.297	1.779	4.126
MCP	88.09%	87.09%	86.51%	80.20%
I. AR / GJR(1,1) - N				
MAE	0.859	-	1.123	-
RMSE	1.352	-	1.775	-
MCP	87.52%	-	86.80%	-
J. AR / GJR(1,1) - T				
MAE	0.857	1.406	1.126	-
RMSE	1.349	2.297	1.776	-
MCP	88.09%	87.23%	86.37%	-
K. AR / GARCH(1,1)-in-mean - N				
MAE	0.868	1.525	1.130	2.524
RMSE	1.372	2.684	1.797	4.383
MCP	86.66%	84.65%	86.23%	78.21%
L. AR / GARCH(1,1)-in-mean - T				
MAE	0.853	1.402	1.136	2.441
RMSE	1.352	2.310	1.834	4.244
MCP	87.52%	86.51%	86.08%	80.06%

The mean absolute prediction error (MAE), the root mean square error (RMSE) and the mean correct prediction (MCP) of the direction of change are reported. For the MCP, the null hypothesis of the sign-test is that the model and the random walk perform equally well, against the alternative that the model under consideration performs better. One asterisk denotes rejection of the null hypothesis at 1% significance levels. The models have been estimated recursively for the period 2 October 2006 to 17 July 2009.

Table 17

Statistical efficiency of the interval forecasts

	BDI	BCI	BPI	TD3
A. Economic Variables				
Violations (%)	20.95	19.66	19.94	14.92
LRunc	215.80*	187.42*	193.61*	96.6*
B. AR				
Violations (%)	25.25	20.23	26.26	8.03
LRunc	320.22*	199.86*	346.63*	11.5*
C. VAR				
Violations (%)	38.31	33.29	41.61	22.81
LRunc	-	550.88*	-	259.26*
D. AR / GARCH(1,1) - N				
Violations (%)	7.75	7.46	7.32	6.46
LRunc	9.55*	7.77*	6.94*	2.86**
E. AR / GARCH(1,1) - T				
Violations (%)	7.32	6.46	7.32	7.89
LRunc	6.93*	2.86*	6.94*	10.51*
F. AR / EGARCH(1,1) - N				
Violations (%)	7.89	7.60	8.18	7.6
LRunc	10.51*	8.64*	12.54*	8.64*
G. AR / EGARCH(1,1) - T				
Violations (%)	7.46	7.17	7.32	7.46
LRunc	7.76*	6.15*	6.94*	7.77*
H. AR / GJR(1,1) - N				
Violations (%)	8.32	-	7.32	-
LRunc	13.61*	-	6.94*	-
I. AR / GJR(1,1) - T				
Violations (%)	7.75	7.32	7.17	-
LRunc	9.56*	6.94*	6.15*	-
J. AR / GARCH(1,1)-in-mean - N				
Violations (%)	8.18	7.60	7.89	6.89
LRunc	12.54*	8.64*	10.51*	4.7*
K. AR / GARCH(1,1)-in-mean - T				
Violations (%)	7.17	6.60	7.60	8.03
LRunc	6.15*	3.43*	8.64*	11.5*

The table reports the percentage of the observations that fall outside the intervals, and the values of Christoffersen's (1998) likelihood ratio test of unconditional coverage (LRunc) for each Baltic Exchange Index. The null hypothesis is that the percentage of times that the actually index prices fall outside the constructed (1-a)% interval forecasts is a%. One and two asterisks denote rejection of the null at 1% and 5% significance level. Results are reported for daily 95% interval forecasts generated by the specific models in each panel. One each day 10.000 bootstrap samples or simulation runs are formed. The models have been estimated recursively for the period 2 October 2006 to 17 July 2009.

Table 18
Modified Diebold-Mariano tests

A. Baltic Dry Index

1) MAE

	RW	Econ	AR(2)	VAR(1)	GARCH-N	GARCH-T	EGARCH-N	EGARCH-T	GJR-N	GJR-T	GARCH-M-N	GARCH-M-T
Econ	-3.74+	-										
AR(2)	-5.56+	-3.36+	-									
VAR(1)	-2.41+	3.27*	5.70*	-								
GARCH-N	-4.81+	-2.69+	0.07	-4.43+	-							
GARCH-T	-5.17+	-3.04+	-0.45	-4.72+	-0.84	-						
EGARCH-N	-4.50+	-2.14++	0.75	-4.03+	1.63	1.49	-					
EGARCH-T	-4.87+	-2.68+	0.39	-4.43+	0.67	2.38**	-0.88	-				
GJR-N	-4.81+	-2.71+	0	-4.43+	-0.37	0.71	-2.03++	-0.88	-			
GJR-T	-5.06+	-3.01+	-0.28	-4.64+	-0.67	0.89	-1.57	-2.99+	-0.56	-		
GARCH-M-N	-4.46+	-1.77	1.08	-3.90+	2.12**	2.04**	0.70	1.37	2.20**	2.03**	-	
GARCH-M-T	-5.44+	-3.05+	-0.74	-4.87+	-0.93	-0.59	-1.43	-1.40	-0.86	-0.76	-1.72	-

2) RMSE

	RW	Econ	AR(2)	VAR(1)	GARCH-N	GARCH-T	EGARCH-N	EGARCH-T	GJR-N	GJR-T	GARCH-M-N	GARCH-M-T
Econ	-2.33++	-										
AR(2)	-3.52+	-2.34++	-									
VAR(1)	-1.43	2.27**	3.80*	-								
GARCH-N	-3.03+	-2.22++	-0.44	-2.99+	-							
GARCH-T	-3.21+	-2.46++	-0.73	-3.13+	-0.54	-						
EGARCH-N	-2.70+	-1.31	0.66	-2.56++	2.17**	1.68	-					
EGARCH-T	-3.05+	-2.15++	-0.15	-2.97+	1.10	1.89	-1.51	-				
GJR-N	-2.97+	-2.12++	-0.27	-2.92+	0.93	0.75	-2.23++	-0.46	-			
GJR-T	-3.13+	-2.40++	-0.55	-3.07+	-0.23	0.97	-1.77	-2.23++	-0.60	-		
GARCH-M-N	-2.67+	-0.79	1.09	-2.41++	1.99**	1.95	0.75	1.67	1.85	1.89	-	
GARCH-M-T	-3.08+	-1.92	-0.19	-2.91+	0.18	0.48	-0.84	-0.12	0.03	0.28	-1.07	-

B. Baltic Capesize Index

1) MAE

	RW	Econ	AR(2)	VAR(1)	GARCH-N	GARCH-T	EGARCH-N	EGARCH-T	GJR-T	GARCH-M-N	GARCH-M-T
Econ	-4.05+	-									
AR(2)	-3.06+	3.36*	-								
VAR(1)	-2.43++	3.98*	1.32	-							
GARCH-N	-5.06+	-1.49	-3.99+	-4.76+	-						
GARCH-T	-4.98+	-1.62	-3.89+	-4.62+	-0.26	-					
EGARCH-N	-4.77+	-1.17	-3.63+	-4.31+	0.96	0.83	-				
EGARCH-T	-5.00+	-2.06++	-4.06+	-4.78+	-0.86	-1.48	-1.38	-			
GJR-T	-4.96+	-1.9	-3.99+	-4.71+	-0.65	-1.23	-1.18	1.13	-		
GARCH-M-N	-1.04	1.18	0.03	-0.17	1.58	1.61	1.5	1.64	1.63	-	
GARCH-M-T	-5.02+	-1.57	-3.80+	-4.54+	-0.62	-0.53	-0.94	-0.19	-0.32	-1.72	-

2) RMSE

	RW	Econ	AR(2)	VAR(1)	GARCH-N	GARCH-T	EGARCH-N	EGARCH-T	GJR-T	GARCH-M-N	GARCH-M-T
Econ	-2.53++	-									
AR(2)	-2.66+	1.2	-								
VAR(1)	-2.31++	1.64	1.54	-							
GARCH-N	-3.32+	-1.76	-1.88	-2.34++	-						
GARCH-T	-3.19+	-1.5	-1.71	-2.14++	0.96	-					
EGARCH-N	-3.06+	-1.36	-1.58	-2.00++	1.04	0.41	-				
EGARCH-T	-3.22+	-1.87	-1.84	-2.27++	0.23	-0.78	-0.85	-			
GJR-T	-3.21+	-1.83	-1.83	-2.25++	0.28	-1.04	-0.79	0.06	-		
GARCH-M-N	0.53	1.09	0.9	0.84	1.25	1.24	1.21	1.24	1.24	-	
GARCH-M-T	-3.04+	-0.94	-1.47	-1.89	0.84	0.56	0.19	0.78	0.79	-1.21	-

Entries report the values of the Modified Diebold-Mariano test (MDM, Harvey et al., 1997) of the relative predictive accuracy of the benchmark model versus the chosen model. The null hypothesis is of equal forecasting accuracy between the chosen model and the benchmark. Two alternative hypotheses H_1 and H_2 are considered. *H1*: the benchmark model outperforms the chosen model and H_2: the chosen model outperforms the benchmark. The models in "rows" are the chosen models and the models in "columns" are the benchmark models. Results are reported for the Baltic Dry Index (Panel A), the Baltic Capesize Index (Panel B), the Baltic Panamax (Panel C) and the Baltic TD3 Index (Panel D.) One and two asterisks (crosses) denote rejection of the null hypothesis in favor of the alternative H_1 (H_2) at 1% and 5% significance level respectively.

Table 18 (conitnued)
Modified Diebold-Mariano tests

C. Baltic Panamax Index

1) MAE

	RW	Econ	AR(2)	VAR(1)	GARCH-N	GARCH-T	EGARCH-N	EGARCH-T	GJR-N	GJR-T	GARCH-M-N	GARCH-M-T
Econ	**-3.74+**	-										
AR(2)	**-5.05+**	**-2.56++**	-									
VAR(1)	**-3.17+**	1.66	**2.90***	-								
GARCH-N	**-4.94+**	**-2.69+**	-0.97	**-2.91+**	-							
GARCH-T	**-4.78+**	**-2.79+**	-0.61	**-2.84+**	0.63	-						
EGARCH-N	**-5.05+**	**-2.78+**	-1.11	**-2.99+**	-0.36	-0.77	-					
EGARCH-T	**-4.74+**	**-2.71+**	-0.46	**-2.82+**	0.68	0.58	0.87	-				
GJR-N	**-4.95+**	**-2.74+**	-1.12	**-2.94+**	-1.51	-1.16	-0.51	-1.13	-			
GJR-T	**-4.77+**	**-2.79+**	-0.66	**-2.86+**	0.37	-0.78	0.53	-1.6	0.84	-		
GARCH-M-N	**-4.88+**	**-2.56++**	-0.38	**-2.76+**	0.69	0.33	0.78	0.19	0.86	0.39	-	
GARCH-M-T	**-4.45+**	**-2.09++**	0.41	**-2.44++**	0.95	0.8	1	0.69	1.06	0.84	0.97	-

2) RMSE

	RW	Econ	AR(2)	VAR(1)	GARCH-N	GARCH-T	EGARCH-N	EGARCH-T	GJR-N	GJR-T	GARCH-M-N	GARCH-M-T
Econ	**-3.00+**	-										
AR(2)	**-3.57+**	**-2.06++**	-									
VAR(1)	**-2.59+**	**1.97****	**2.78***	-								
GARCH-N	**-3.36+**	**-2.34++**	-1.29	**-2.66+**	-							
GARCH-T	**-3.24+**	**-2.29++**	-1.21	**-2.58+**	-0.02	-						
EGARCH-N	**-3.44+**	**-2.47++**	-1.36	**-2.75+**	0.18	0.09	-					
EGARCH-T	**-3.18+**	**-2.17++**	-1.08	**-2.54++**	0.37	0.97	0.27	-				
GJR-N	**-3.33+**	**-2.32++**	-1.3	**-2.65+**	-0.65	-0.27	-0.45	-0.64	-			
GJR-T	**-3.20+**	**-2.24++**	-1.17	**-2.56++**	0.05	0.26	-0.03	-1.42	0.3	-		
GARCH-M-N	**-3.84+**	**-2.16++**	-0.91	**-2.81+**	0.78	0.72	0.81	0.6	0.79	0.69	-	
GARCH-M-T	**-3.33+**	-0.05	0.69	-1.77	1.01	0.99	1.04	0.94	1.02	0.98	1.16	-

D. Baltic TD3 Route

1) MAE

	RW	Econ	AR(1)	VAR(1)	GARCH-N	GARCH-T	EGARCH-N	EGARCH-T	GARCH-M-N	GARCH-M-T
Econ	**-5.87+**	-								
AR(2)	**-6.04+**	-1.37	-							
VAR(1)	**-5.38+**	0.77	1.25	-						
GARCH-N	**-6.74+**	1.32	1.72	0.52	-					
GARCH-T	**-5.71+**	**-3.16+**	**-2.79+**	**-2.67+**	**-2.67+**	-				
EGARCH-N	**-6.42+**	0.27	0.25	-0.85	**-3.12+**	**2.04****	-			
EGARCH-T	**-5.58+**	**-3.16+**	**-2.84+**	**-2.86+**	**-2.66+**	**-2.25++**	**-2.15++**	-		
GARCH-M-N	**-5.45+**	1.67	1.9	1.18	1.17	**2.41****	**1.97****	**2.47****	-	
GARCH-M-T	**-5.73+**	-0.82	-0.51	-1.12	-1.74	0.96	-0.97	1.24	**-2.98+**	-

2) RMSE

	RW	Econ	AR(1)	VAR(1)	GARCH-N	GARCH-T	EGARCH-N	EGARCH-T	GARCH-M-N	GARCH-M-T
Econ	**-2.84+**	-								
AR(2)	**-2.88+**	-0.1	-							
VAR(1)	**-2.76+**	0.43	0.44	-						
GARCH-N	**-3.41+**	1.26	1.33	1.06	-					
GARCH-T	**-2.68+**	-1.24	-1.15	-1.38	-1.35	-				
EGARCH-N	**-3.14+**	0.78	0.87	0.49	-1.66	1.13	-			
EGARCH-T	**-2.59+**	-1.07	-1.01	-1.25	-1.26	-0.52	-1.04	-		
GARCH-M-N	**-2.78+**	1.24	1.26	1.17	1.14	1.27	1.27	1.24	-	
GARCH-M-T	**-3.38+**	0.95	0.99	0.83	0.25	1.08	0.88	1.05	-1.41	-

Entries report the values of the Modified Diebold-Mariano test (MDM, Harvey et al., 1997) of the relative predictive accuracy of the benchmark model versus the chosen model. The null hypothesis is of equal forecasting accuracy between the chosen model and the benchmark. Two alternative hypotheses H_1 and H_2 are considered. *H1*: the benchmark model outperforms the chosen model and H_2: the chosen model outperforms the benchmark. The models in "rows" are the chosen models and the models in "columns" are the benchmark models. Results are reported for the Baltic Dry Index (Panel A), the Baltic Capesize Index (Panel B), the Baltic Panamax (Panel C) and the Baltic TD3 Index (Panel D.) One and two asterisks (crosses) denote rejection of the null hypothesis in favor of the alternative H_1 (H_2) at 1% and 5% significance level respectively.

In the case of the interval forecasts, Table 17 shows the percentage of observations that fall outside the constructed 95% interval forecasts (Violations). Moreover, we observe that violations in all cases are above 5%, which is the significance level. The each Baltic index, the highest violations occur in the VAR models. The highest percentage of times that a Baltic index violates the constructed intervals is reported for the VAR (1) model in the BPI (41.61%). Therefore, we reject the null hypothesis of efficient interval forecasts in all instances.

5.3 Out-of-sample Evidence: Economic Significance

In the previous section the reported results on point forecasts suggest that there is a strong evidence of a statistically predictable pattern in the evolution of the four Baltic exchange indices. However, none of the 95% bootstrapped interval forecasts were found to be efficient. We examine the economic significance of these patterns by performing trading strategies on point and interval forecasts using all futures maturities.

Tables 19 – 24 present the Sharpe Ratio, Leland's Alpha and their respective bootstrapped 95% confidence intervals (CI) for the BCI, BPI and the TD3 for the trading strategies using IMAREX Futures from different maturities. Unfortunately, freight futures on Baltic Dry were recently introduced, thus we cannot use them for trading strategies.

In Tables 19-20 results of the trading strategies for the BCI are reported based on point and interval forecasts respectively. In table 19 we observe that the SR is significant only in four models using the shortest maturity contracts. The A_p are significant in six cases. Furthermore, the performance measures are insignificant in all cases for the other maturities. The performance measures are significant for the trading strategies based on interval forecasts only for the Economic variables model, VAR(1) and AR(2). These results imply that certain trading strategies based on point and interval forecasts do yield economically significant profits for the BCI.

In Tables 21-22 results of the trading strategies for the BPI are reported based on point and interval forecasts respectively. As far as the point forecasts are concerned, results of SR and A_p indicate profitable strategies when using the first shortest IMAREX contracts. Trading strategies using longer futures maturities do not yield significant profits. In table 22, we observe that only the case of the AR(2) model has significantly positive performance measures. Overall, trading strategies for the BPI are only profitable in the case of the point forecasts.

In tables 23-24 performance measures for the trading strategies on point and interval forecasts on the TD3 route are reported. In table 23 for trading strategies on point forecasts, it is easily observable that in all cases we accept the hypothesis of profitable strategies under the Sharpe ratio (SR) and the Leland Alpha (*Ap*). More surprising is that trading strategies are still profitable even for longer maturities, although the performance measures are smaller for longer maturities. Similarly, for the interval forecasts in all cases under the SR and the *Ap* are significant. Thus, we find clear results for profitable trading strategies on the TD3 both based on point and interval forecasts.

Table 19
Trading strategy with IMAREX futures based on point forecasts for BCI

Baltic Capesize Index				
	1st Shortest	**2nd Shortest**	**3rd Shortest**	**4th Shortest**
A. Economic Variables				
Sharpe Ratio	0.0786	-0.0304	-0.0363	-0.0339
95% CI	(-0.01, 0.16)	(-0.12, 0.06)	(-0.13, 0.06)	(-0.13, 0.06)
A_p	0.0055	-0.002	-0.0021	-0.0019
95% CI	(-0.001, 0.012)	(-0.007, 0.004)	(-0.007, 0.004)	(-0.007, 0.005)
B. AR(2)				
Sharpe Ratio	0.0571	-0.0556	-0.0717	-0.0672
95% CI	(-0.04, 0.14)	(-0.15, 0.03)	(-0.16, 0.02)	(-0.16, 0.03)
A_p	0.004	-0.0036	-0.0041	-0.0038
95% CI	(-0.003, 0.011)	(-0.009, 0.002)	(-0.009, 0.001)	(-0.009, 0.002)
C. VAR(1)				
Sharpe Ratio	0,048	-0,071	-0,089	-0,082
95% CI	(-0.05, 0.14)	(-0.17, 0.02)	(-0.19, 0.01)	(-0.19, 0.03)
A_p	0,0033	-0,0046	-0,0051	-0,0046
95% CI	(-0.003, 0.01)	(-0.01, 0.001)	(-0.011, 0.001)	(-0.01, 0.002)
D. AR / GARCH(1,1) - N				
Sharpe Ratio	0.0944	-0.0158	-0.0228	-0.0185
95% CI	(0.01, 0.17)	(-0.11, 0.07)	(-0.11, 0.06)	(-0.11, 0.08)
A_p	0.0066	-0.001	-0.0013	-0.001
95% CI	(0.001, 0.013)	(-0.006, 0.004)	(-0.006, 0.004)	(-0.006, 0.005)
E. AR / GARCH(1,1) - T				
Sharpe Ratio	0.0946	-0.0128	-0.018	-0.0128
95% CI	(0.01, 0.17)	(-0.10, 0.07)	(-0.11, 0.08)	(-0.10, 0.08)
A_p	0.0066	-0.0008	-0.001	-0.0007
95% CI	(0.001, 0.01)	(-0.006, 0.004)	(-0.006, 0.004)	(-0.006, 0.005)
F. AR / EGARCH(1,1) - N				
Sharpe Ratio	0.0887	-0.0076	-0.0215	-0.0073
95% CI	(0, 0.17)	(-0.10, 0.07)	(-0.11, 0.06)	(-0.10, 0.09)
A_p	0.0062	-0.0005	-0.0012	-0.0004
95% CI	(0.001, 0.011)	(-0.006, 0.004)	(-0.006, 0.004)	(-0.006, 0.005)
G. AR / EGARCH(1,1) - T				
Sharpe Ratio	0.0065	-0.0009	-0.001	-0.0007
95% CI	(0.01, 0.18)	(-0.10, 0.07)	(-0.11, 0.07)	(-0.11, 0.08)
A_p	0.0066	-0.0008	-0.001	-0.0007
95% CI	(0.001, 0.01)	(-0.006, 0.004)	(-0.006, 0.004)	(-0.006, 0.005)
H. AR / GJR(1,1) - T				
Sharpe Ratio	0.095	-0.0124	-0.0176	-0.0124
95% CI	(0.02, 0.17)	(-0.10, 0.07)	(-0.11, 0.07)	(-0.10, 0.09)
A_p	0.0066	-0.0008	-0.001	-0.0007
95% CI	(0.001, 0.013)	(-0.006, 0.004)	(-0.006, 0.004)	(-0.006, 0.005)
I. AR / GARCH(1,1)-in-mean - N				
Sharpe Ratio	0.089	-0.0119	-0.0112	-0.0073
95% CI	(0, 0.17)	(-0.10, 0.07)	(-0.10, 0.07)	(-0.10, 0.09)
A_p	0.0062	-0.0008	-0.0007	-0.0004
95% CI	(0, 0.014)	(-0.005, 0.005)	(-0.006, 0.004)	(-0.006, 0.005)
J. AR / GARCH(1,1)-in-mean - T				
Sharpe Ratio	0.0792	-0.014	-0.0274	-0.0146
95% CI	(-0.01, 0.16)	(-0.10, 0.07)	(-0.11, 0.06)	(-0.11, 0.08)
A_p	0.0055	-0.0009	-0.0016	-0.0008
95% CI	(-0.001, 0.013)	(-0.006, 0.004)	(-0.006, 0.004)	(-0.006, 0.005)

The Sharpe ratio (SR), the Leland's alpha (A_p) and their respective bootstrapped 95% confidence intervals (95% CI) in parentheses. The strategy is based on point forecasts obtained from all models foe Baltic Capesize Index

Table 20
Trading strategy with IMAREX futures based on interval forecasts for BCI

Baltic Capesize Index	1st Shortest	2nd Shortest	3rd Shortest	4th Shortest
A. Economic Variables				
Sharpe Ratio	0.146	0.0986	0.1051	0.1007
95% CI	(0.07, 0.22)	(0.01, 0.19)	(0.02, 0.19)	(0.01, 0.19)
A_p	0.0101	0.0064	0.006	0.0056
95% CI	(0.004, 0.017)	(0.001, 0.012)	(0.001, 0.011)	(0.001, 0.011)
B. AR(2)				
Sharpe Ratio	0.1709	0.1877	0.1645	0.1546
95% CI	(0.10, 0.24)	(0.11, 0.26)	(0.09, 0.24)	(0.08, 0.23)
A_p	0.0118	0.0119	0.0093	0.0085
95% CI	(0.006, 0.017)	(0.007, 0.016)	(0.005, 0.013)	(0.004, 0.013)
C. VAR(1)				
Sharpe Ratio	0.1568	0.0599	0.0659	0.0707
95% CI	(0.07, 0.24)	(-0.03, 0.15)	(-0.02, 0.15)	(-0.02, 0.17)
A_p	0.0108	0.0039	0.0037	0.0039
95% CI	(0.005, 0.018)	(-0.001, 0.01)	(-0.001, 0.01)	(-0.001, 0.009)
D. AR / GARCH(1,1) - N				
Sharpe Ratio	0.0353	-0.0952	-0.0994	-0.0868
95% CI	(-0.06, 0.12)	(-0.19, 0)	(-0.20, -0.01)	(-0.19, 0.01)
A_p	0.0025	-0.0062	-0.0057	-0.0049
95% CI	(-0.004, 0.009)	(-0.011, -0.001)	(-0.011, -0.001)	(-0.011, 0)
E. AR / GARCH(1,1) - T				
Sharpe Ratio	0.0338	-0.0919	-0.1122	-0.1044
95% CI	(-0.06, 0.12)	(-0.19, 0)	(-0.21, -0.02)	(-0.21, 0.01)
A_p	0.0024	-0.0059	-0.0064	-0.0058
95% CI	(-0.004, 0.009)	(-0.012, -0.001)	(-0.011, -0.001)	(-0.011, 0)
F. AR / EGARCH(1,1) - N				
Sharpe Ratio	0.0265	-0.0922	-0.1054	-0.0969
95% CI	(-0.07, 0.12)	(-0.19, 0)	(-0.21, -0.01)	(-0.20, 0)
A_p	0.0019	-0.006	-0.006	-0.0054
95% CI	(-0.004, 0.009)	(-0.012, -0.001)	(-0.011, -0.001)	(-0.011, 0)
G. AR / EGARCH(1,1) - T				
Sharpe Ratio	0.0397	-0.0785	-0.0964	-0.0888
95% CI	(-0.06, 0.13)	(-0.19, 0.02)	(-0.20, 0)	(-0.20, 0.03)
A_p	0.0028	-0.0051	0.006	0.0056
95% CI	(-0.003, 0.01)	(-0.011, -0.001)	(-0.011, -0.001)	(-0.011, 0.001)
H. AR / GJR(1,1) - T				
Sharpe Ratio	0.0427	-0.0721	-0.0908	-0.0857
95% CI	(-0.06, 0.13)	(-0.17, 0.02)	(-0.20, 0.01)	(-0.20, 0.03)
A_p	0.003	-0.0047	-0.0052	-0.0048
95% CI	(-0.004, 0.01)	(-0.01, -0.002)	(-0.011, -0.001)	(-0.011, 0.002)
I. AR / GARCH(1,1)-in-mean - N				
Sharpe Ratio	0.0562	-0.0681	-0.075	-0.0642
95% CI	(-0.04, 0.14)	(-0.16, 0.02)	(-0.17, 0.01)	(-0.17, 0.03)
A_p	0.0039	-0.0044	-0.0043	-0.0036
95% CI	(-0.002, 0.01)	(-0.01, -0.002)	(-0.01, -0.001)	(-0.009, 0.002)
J. AR / GARCH(1,1)-in-mean - T				
Sharpe Ratio	0.0452	-0.078	-0.0958	-0.0868
95% CI	(-0.05, 0.13)	(-0.17, 0.01)	(-0.19, 0)	(-0.19, 0.02)
A_p	0.0032	-0.005	-0.0055	-0.0049
95% CI	(-0.002, 0.01)	(-0.011, -0.001)	(-0.011, 0.002)	(-0.01, 0.001)

The Sharpe ratio (SR), the Leland's alpha (A_p) and their respective bootstrapped 95% confidence intervals (95% CI) in parentheses. The strategy is based on interval forecasts obtained from all models foe Baltic Capesize Index

Table 21
Trading strategy with IMAREX futures based on point forecasts for BPI

Baltic Panamax Index				
	1st Shortest	**2nd Shortest**	**3rd Shortest**	**4th Shortest**
A. Economic Variables				
Sharpe Ratio	0.0828	0.0111	-0.0417	-0.0417
95% CI	(0, 0.18)	(-0.08, 0.10)	(-0.12, 0.04)	(-0.12, 0.04)
A_p	0.0048	0.0006	-0.0021	-0.002
95% CI	(0, 0.01)	(-0.004, 0.005)	(-0.006, 0.002)	(-0.006, 0.002)
B. AR(2)				
Sharpe Ratio	0.1125	0.0084	-0.0524	-0.0298
95% CI	(0.04, 0.18)	(-0.07, 0.09)	(-0.13, 0.03)	(-0.11, 0.05)
A_p	0.0066	0.0004	-0.0027	-0.0015
95% CI	(0.002, 0.011)	(-0.004, 0.005)	(-0.006, 0.002)	(-0.006, 0.002)
C. VAR(1)				
Sharpe Ratio	0.096	-0.0152	-0.079	-0.0607
95% CI	(0.02, 0.18)	(-0.10, 0.07)	(-0.15, 0)	(-0.14, 0.02)
A_p	0.0056	-0.0008	-0.004	-0.0029
95% CI	(0.001, 0.01)	(-0.005, 0.004)	(-0.008, 0)	(-0.008, 0.001)
D. AR / GARCH(1,1) - N				
Sharpe Ratio	0.1245	0.0083	-0.0471	-0.0261
95% CI	(0.05, 0.20)	(-0.08, 0.09)	(-0.12, 0.03)	(-0.10, 0.06)
A_p	0.0073	0.0004	-0.0024	-0.0013
95% CI	(0.003, 0.012)	(-0.004, 0.005)	(-0.006, 0.002)	(-0.005, 0.002)
E. AR / GARCH(1,1) - T				
Sharpe Ratio	0.1173	0.0114	-0.0491	-0.0264
95% CI	(0.04, 0.19)	(-0.07, 0.09)	(-0.12, 0.03)	(-0.11, 0.05)
A_p	0.0069	0.0006	-0.0025	-0.0013
95% CI	(0.002, 0.011)	(-0.004, 0.005)	(-0.006, 0.002)	(-0.005, 0.003)
F. AR / EGARCH(1,1) - N				
Sharpe Ratio	0.1182	0.0123	-0.0484	-0.0257
95% CI	(0.04, 0.19)	(-0.07, 0.09)	(-0.12, 0.03)	(-0.11, 0.06)
A_p	0.0069	0.0007	-0.0025	-0.0013
95% CI	(0.003, 0.012)	(-0.004, 0.005)	(-0.006, 0.001)	(-0.005, 0.003)
G. AR / EGARCH(1,1) - T				
Sharpe Ratio	0.1193	0.0139	-0.0474	-0.0248
95% CI	(0.05, 0.19)	(-0.07, 0.10)	(-0.12, 0.03)	(-0.10, 0.06)
A_p	0.007	0.0008	-0.0024	-0.0012
95% CI	(0.003, 0.011)	(-0.004, 0.005)	(-0.006, 0.001)	(-0.005, 0.003)
H. AR / GJR(1,1) - N				
Sharpe Ratio	0.121	0.0133	-0.0471	-0.0239
95% CI	(0.05, 0.20)	(-0.07, 0.10)	(-0.12, 0.03)	(-0.10, 0.06)
A_p	0.0071	0.0007	-0.0024	-0.0012
95% CI	(0.002, 0.012)	(-0.004, 0.005)	(-0.006, 0.001)	(-0.005, 0.003)
I. AR / GJR(1,1) - T				
Sharpe Ratio	0.113	0.0119	-0.0485	-0.0257
95% CI	(0.04, 0.19)	(-0.07, 0.10)	(-0.12, 0.03)	(-0.10, 0.05)
A_p	0.0066	0.0006	-0.0025	-0.0013
95% CI	(0.002, 0.011)	(-0.004, 0.005)	(-0.006, 0.001)	(-0.005, 0.003)
J. AR / GARCH(1,1)-in-mean - N				
Sharpe Ratio	0.1189	0.0173	-0.0407	-0.0169
95% CI	(0.05, 0.19)	(-0.07, 0.10)	(-0.12, 0.04)	(-0.10, 0.07)
A_p	0.0069	0.0009	-0.0021	-0.0008
95% CI	(0.002, 0.012)	(-0.004, 0.006)	(-0.006, 0.002)	(-0.005, 0.003)
K. AR / GARCH(1,1)-in-mean - T				
Sharpe Ratio	0.1176	0.0157	-0.0447	-0.0202
95% CI	(0.04, 0.19)	(-0.07, 0.09)	(-0.13, 0.04)	(-0.10, 0.07)
A_p	0.0069	0.0008	-0.0023	-0.001
95% CI	(0.002, 0.011)	(-0.004, 0.005)	(-0.006, 0.001)	(-0.005, 0.003)

The Sharpe ratio (SR), the Leland's alpha (A_p) and their respective bootstrapped 95% confidence intervals (95% CI) in parentheses. The strategy is based on point forecasts obtained from all models foe Baltic Panamax Index

Table 22

Trading strategy with IMAREX futures based on interval forecasts for BPI

Baltic Panamax Index				
	1st Shortest	**2nd Shortest**	**3rd Shortest**	**4th Shortest**
A. Economic Variables				
Sharpe Ratio	0.0321	0.0442	-0.0026	0.0142
95% CI	(-0.04, 0.12)	(-0.04, 0.12)	(-0.08, 0.07)	(-0.06, 0.09)
A_p	0.0019	0.0024	-0.0002	0.0006
95% CI	(-0.003, 0.006)	(-0.002, 0.006)	(-0.004, 0.003)	(-0.003, 0.004)
B. AR(2)				
Sharpe Ratio	0.0964	0.0853	0.0229	0.0546
95% CI	(0.03, 0.16)	(0.01, 0.15)	(-0.05, 0.10)	(-0.01, 0.13)
A_p	0.0056	0.0046	0.0011	0.0026
95% CI	(0.001, 0.01)	(0, 0.009)	(-0.002, 0.004)	(-0.001, 0.006)
C. VAR(1)				
Sharpe Ratio	0.072	0.0061	-0.0567	-0.0478
95% CI	(0, 0.17)	(-0.07, 0.08)	(-0.13, 0.01)	(-0.13, 0.04)
A_p	0.0042	0.0003	-0.0029	-0.0023
95% CI	(-0.001, 0.009)	(-0.004, 0.005)	(-0.007, 0.001)	(-0.006, 0.001)
D. AR / GARCH(1,1) - N				
Sharpe Ratio	-0.0426	-0.0895	-0.14	-0.1421
95% CI	(-0.11, 0.04)	(-0.17, 0)	(-0.22, -0.07)	(-0.22, -0.07)
A_p	-0.0025	-0.0048	-0.0071	-0.0069
95% CI	(-0.007, 0.002)	(-0.009, 0)	(-0.01, -0.003)	(-0.01, -0.003)
E. AR / GARCH(1,1) - T				
Sharpe Ratio	-0.0465	-0.0949	-0.1471	-0.1485
95% CI	(-0.11, 0.03)	(-0.17,-0.01)	(-0.22, -0.07)	(-0.22, -0.08)
A_p	-0.0028	-0.0051	-0.0074	-0.0072
95% CI	(-0.007, 0.002)	(-0.009, 0)	(-0.011, -0.003)	(-0.011, -0.003)
F. AR / EGARCH(1,1) - N				
Sharpe Ratio	-0.0441	-0.0899	-0.1402	-0.1452
95% CI	(-0.11, 0.03)	(-0.18, 0)	(-0.22, -0.06)	(-0.22, -0.07)
A_p	-0.0026	-0.0049	-0.0071	-0.007
95% CI	(-0.007, 0.002)	(-0.009, 0)	(-0.011, -0.003)	(-0.011, -0.003)
G. AR / EGARCH(1,1) - T				
Sharpe Ratio	-0.0288	-0.0841	-0.1351	-0.1435
95% CI	(-0.10, 0.05)	(-0.17,-0.01)	(-0.21, -0.06)	(-0.22, -0.07)
A_p	-0.0017	-0.0045	-0.0068	-0.0069
95% CI	(-0.007, 0.003)	(-0.009, 0)	(-0.011, -0.003)	(-0.011, -0.003)
H. AR / GJR(1,1) - N				
Sharpe Ratio	-0.0442	-0.0888	-0.1385	-0.1432
95% CI	(-0.11, 0.03)	(-0.17, 0)	(-0.22, -0.06)	(-0.22, -0.07)
A_p	-0.0026	-0.0048	-0.007	-0.0069
95% CI	(-0.007, 0.002)	(-0.009, 0)	(-0.011, -0.003)	(-0.01, -0.003)
I. AR / GJR(1,1) - T				
Sharpe Ratio	-0.0082	-0.0823	-0.1174	-0.1174
95% CI	(-0.08, 0.07)	(-0.17, 0)	(-0.20, -0.04)	(-0.22, -0.076)
A_p	-0.0005	-0.0045	-0.006	-0.0068
95% CI	(-0.005, 0.004)	(-0.009, 0)	(-0.01, 0)	(-0.01, -0.003)
J. AR / GARCH(1,1)-in-mean - N				
Sharpe Ratio	-0.0325	-0.093	-0.1269	-0.1481
95% CI	(-0.10, 0.04)	(-0.18, 0)	(-0.21, -0.04)	(-0.22, -0.07)
A_p	-0.0019	-0.005	-0.0064	-0.0071
95% CI	(-0.006, 0.003)	(-0.01, 0)	(-0.011, -0.002)	(-0.011, -0.003)
K. AR / GARCH(1,1)-in-mean - T				
Sharpe Ratio	-0.0286	-0.0917	-0.1305	-0.1517
95% CI	(-0.10, 0.05)	(-0.18, 0)	(-0.22, -0.05)	(-0.23, -0.07)
A_p	-0.0017	-0.005	-0.0066	-0.0073
95% CI	(-0.006, 0.003)	(-0.01, 0)	(-0.011, -0.002)	(-0.011, -0.003)

The Sharpe ratio (SR), the Leland's alpha (A_p) and their respective bootstrapped 95% confidence intervals (95% CI) in parentheses. The strategy is based on interval forecasts obtained from all models foe Baltic Panamax Index

Table 23

Trading strategy with IMAREX futures based on point forecasts for TD3

Baltic TD3 Index				
	1st Shortest	**2nd Shortest**	**3rd Shortest**	**4th Shortest**
A. Economic Variables				
Sharpe Ratio	0.2933	0.2275	0.2039	0.1177
95% CI	(0.23, 0.36)	(0.15, 0.30)	(0.13, 0.27)	(0.03, 0.20)
A_p	0.0183	0.0126	0.0094	0.0044
95% CI	(0.014, 0.022)	(0.008, 0.017)	(0.006, 0.013)	(0.001, 0,007)
B. AR(1)				
Sharpe Ratio	0.2859	0.2215	0.1966	0.1078
95% CI	(0.22, 0.35)	(0.15, 0.30)	(0.12, 0.27)	(0.03, 0.19)
A_p	0.0179	0.0123	0.0091	0.0041
95% CI	(0.014, 0.022)	(0.008, 0.017)	(0.006, 0.013)	(0.001, 0,007)
C. VAR(1)				
Sharpe Ratio	0.2872	0.2284	0.1931	0.1125
95% CI	(0.22, 0.36)	(0.16, 0.30)	(0.12, 0.26)	(0.03, 0.20)
A_p	0.0179	0.0126	0.0089	0.0042
95% CI	(0.014, 0.022)	(0.009, 0.017)	(0.005, 0.013)	(0.001, 0,007)
D. AR / GARCH(1,1) - N				
Sharpe Ratio	0.2742	0.208	0.1944	0.1223
95% CI	(0.21, 0.34)	(0.14, 0.28)	(0.12, 0.26)	(0.04, 0.21)
A_p	0.0172	0.0116	0.009	0.0046
95% CI	(0.012, 0.021)	(0.007, 0.016)	(0.006, 0.013)	(0.002, 0,007)
E. AR / GARCH(1,1) - T				
Sharpe Ratio	0.2726	0.2081	0.1934	0.1121
95% CI	(0.21, 0.34)	(0.13, 0.28)	(0.12, 0.26)	(0.03, 0.20)
A_p	0.0171	0.0116	0.0089	0.0042
95% CI	(0.012, 0.022)	(0.007, 0.016)	(0.006, 0.012)	(0.001, 0,007)
F. AR / EGARCH(1,1) - N				
Sharpe Ratio	0.2674	0.1937	0.1665	0.1028
95% CI	(0.2, 0.34)	(0.12, 0.26)	(0.10, 0.23)	(0.02, 0.18)
A_p	0.0168	0.0108	0.0077	0.0039
95% CI	(0.012, 0.021)	(0.006, 0.015)	(0.005, 0.012)	(0.001, 0,007)
G. AR / EGARCH(1,1) - T				
Sharpe Ratio	0.2717	0.2076	0.1886	0.1085
95% CI	(0.21, 0.34)	(0.13, 0.28)	(0.12, 0.25)	(0.03, 0.19)
A_p	0.0171	0.0116	0.0087	0.0041
95% CI	(0.012, 0.021)	(0.007, 0.016)	(0.005, 0.012)	(0.001, 0,007)
H. AR / GARCH(1,1)-in-mean - N				
Sharpe Ratio	0.2817	0.2093	0.1855	0.1173
95% CI	(0.21, 0.35)	(0.13, 0.28)	(0.11, 0.26)	(0.04, 0.20)
A_p	0.0176	0.0117	0.0086	0.0044
95% CI	(0.013, 0.022)	(0.007, 0.016)	(0.005, 0.012)	(0.001, 0,007)
I. AR / GARCH(1,1)-in-mean - T				
Sharpe Ratio	0.2855	0.2223	0.1997	0.1111
95% CI	(0.22, 0.35)	(0.15, 0.30)	(0.13, 0.27)	(0.03, 0.19)
A_p	0.0178	0.0124	0.0092	0.0042
95% CI	(0.013, 0.022)	(0.008, 0.017)	(0.005, 0.012)	(0.001, 0,007)

The Sharpe ratio (SR), the Leland's alpha (A_p) and their respective bootstrapped 95% confidence intervals (95% CI) in parentheses. The strategy is based on point forecasts obtained from all models for Baltic TD3 Route.

Table 24

Trading strategy with IMAREX futures based on interval forecasts for TD3

Baltic TD3 Index				
	1st Shortest	**2nd Shortest**	**3rd Shortest**	**4th Shortest**
A. Economic Variables				
Sharpe Ratio	0.3221	0.2697	0.2264	0.1515
95% CI	(0.26, 0.38)	(0.20, 0.34)	(0.15, 0.30)	(0.07, 0.24)
A_p	0.0199	0.0149	0.0104	0.0057
95% CI	(0.015, 0.024)	(0.011, 0.019)	(0.007, 0.014)	(0.003, 0,008)
B. AR(1)				
Sharpe Ratio	0.2675	0.285	0.2367	0.2092
95% CI	(0.21, 0.33)	(0.21, 0.35)	(0.16, 0.31)	(0.14, 0.27)
A_p	0.0168	0.0157	0.0109	0.0078
95% CI	(0.012, 0.021)	(0.011, 0.02)	(0.007, 0.015)	(0.005, 0,01)
C. VAR(1)				
Sharpe Ratio	0.2917	0.2226	0.2062	0.1234
95% CI	(0.23, 0.36)	(0.15, 0.30)	(0.14, 0.27)	(0.04, 0.21)
A_p	0.0182	0.0124	0.0095	0.0047
95% CI	(0.014, 0.023)	(0.008, 0.016)	(0.006, 0.013)	(0.002, 0,007)
D. AR / GARCH(1,1) - N				
Sharpe Ratio	0.2832	0.2152	0.1974	0.1168
95% CI	(0.22, 0.35)	(0.14, 0.29)	(0.13, 0.27)	(0.04, 0.21)
A_p	0.0178	0.012	0.0092	0.0044
95% CI	(0.013, 0.023)	(0.008, 0.016)	(0.006, 0.013)	(0.001, 0,007)
E. AR / GARCH(1,1) - T				
Sharpe Ratio	0.2786	0.1816	0.1538	0.1069
95% CI	(0.21, 0.34)	(0.10, 0.26)	(0.08, 0.24)	(0.03, 0.19)
A_p	0.0175	0.0102	0.0072	0.004
95% CI	(0.012, 0.023)	(0.008, 0.016)	(0.006, 0.013)	(0.001, 0,007)
F. AR / EGARCH(1,1) - N				
Sharpe Ratio	0.2764	0.1924	0.1653	0.0904
95% CI	(0.21, 0.34)	(0.12, 0.26)	(0.09, 0.24)	(0.02, 0.18)
A_p	0.0174	0.0108	0.0077	0.0034
95% CI	(0.013, 0.022)	(0.007, 0.015)	(0.004, 0.011)	(0.001, 0,006)
G. AR / EGARCH(1,1) - T				
Sharpe Ratio	0.2791	0.2161	0.1868	0.1024
95% CI	(0.21, 0.34)	(0.14, 0.29)	(0.11, 0.26)	(0.02, 0.19)
A_p	0.0175	0.012	0.0087	0.0039
95% CI	(0.013, 0.022)	(0.008, 0.016)	(0.005, 0.012)	(0.001, 0,006)
H. AR / GARCH(1,1)-in-mean - N				
Sharpe Ratio	0.2569	0.2048	0.1868	0.1088
95% CI	(0.19, 0.32)	(0.13, 0.27)	(0.12, 0.26)	(0.03, 0.19)
A_p	0.0162	0.0115	0.0087	0.0041
95% CI	(0.011, 0.02)	(0.007, 0.015)	(0.005, 0.012)	(0.001, 0,007)
I. AR / GARCH(1,1)-in-mean - T				
Sharpe Ratio	0.2761	0.1875	0.1617	0.0994
95% CI	(0.21, 0.35)	(0.11, 0.26)	(0.09, 0.24)	(0.02, 0.18)
A_p	0.0173	0.0105	0.0075	0.0038
95% CI	(0.013, 0.022)	(0.006, 0.014)	(0.004, 0.011)	(0.001, 0,006)

The Sharpe ratio (SR), the Leland's alpha (A_p) and their respective bootstrapped 95% confidence intervals (95% CI) in parentheses. The strategy is based on interval forecasts obtained from all models for Baltic TD3 Route.

Chapter 6

IMAREX Freight Futures: Results and Discussion

6.1 In-Sample Evidence

Tables 25 – 27 present the in-sample performance of the economic variables, ARMA, VAR and GARCH-family models and the estimated coefficients for the IMAREX Capesize (T/C Basket) Futures.

Table 25 reports the in-sample performance of the economic variables model. The set of the economic variables was augmented with lagged terms of the futures maturity and the Baltic Capesize Index. The table shows the coefficients of the regression, the AIC and BIC values and the adjusted R^2. The R^2 takes the largest value for the shortest futures maturity (6.55%). These values are significantly smaller than the spot rates. This is similar to the values of adjusted R^2 documented by previous related literature; see for instance Batchelor et al. (2007).

Table 25

Forecasting IMAREX Capesize Futures with the Economic Variables model

	1st Shortest	2nd Shortest	3rd Shortest	4th Shortest
c	0.002	0.002	0.004	0.0012
	(0.915)	(1.084)	(1.739)	(0.399)
AR(1)	**0.239***	**0.21***	0.158	**0.13****
	(3.057)	(2.783)	(1.669)	(2.566)
BCI_{t-1}	0.105	0.022	-0.01	0.013
	(0.786)	(0.14)	(-0.077)	(0.098)
$Coal_{t-1}$	-0.0002	-0.0009	-0.0003	-0.002
	(-0.106)	(-0.719)	(-0.191)	(-0.353)
IM_{t-1}	-0.001	-0.001	-0.0008	-0.0006
	(-0.972)	(-1.032)	(-0.68)	(-0.496)
i_{t-1}	-0.0058	-0.006	**-0.016****	0.0018
	(-0.768)	(-0.925)	(-2.309)	(0.188)
ys_{t-1}	-0.005	-0.006	-0.006	-0.007
	(-1.212)	(-1.449)	(-1.349)	(-1.4)
AIC	-1335.10	-1345.00	-1317.3	-1170.60
BIC	-1303.40	-1313.65	-1286.23	-1139.20
Adj. R^2	0.0655	0.0467	0.0295	0.0076

The entries report results from the estimation of the economic variables models for the daily changes of the IMAREX Capesize Futures. AR: a lagged term of IMAREX Capesize Futures, BCI: spot returns of BCI, c: a constant, Coal: the log-return of coal prices, IM : log-returns of the S&P GSCI Industrial Metals index, i: the one month Libor rate in log-differences, ys: the slope of the yield curve calculated as the difference between the prices of the ten year U.S. government bond and the one-month interbank rate. The estimated coefficients, Newey-West t-statistics in parenthesis, the Akaike and Bayesian information criterion and the adjusted R^2 are reported. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% level. The models have been estimated for the period 5 April 2005 to 29 September 2006.

Table 26 presents the in-sample performance for the univariate ARMA models, VAR models and the ARMA models with GARCH error processes for two probability functions. The lag length for the autoregressive and moving average parts are chosen to minimize BIC criterion. We observe that all models seem to have low coefficients of determination. The highest R^2 are referred for the shortest maturity.

Table 27 reports the in-sample performance for the univariate ARMA models with EGARCH and GJR error processes and GARCH-In-Mean models. GJR models could not be specified for any maturity. For our model selection, we choose the lag length that minimizes BIC criterion. These three GARCH-family models are estimated for two alternative conditional probability density functions of the indices returns: Normal distribution and the Student-t distribution. These models also have low adjusted R^2 values. The highest R^2 value is referred for GARCH-In-Mean – T (7.99%). These values of the coefficient of determination indicate that there is a weakly predictable pattern for the IMAREX Capesize Futures.

Table 27

Forecasting IMAREX Capesize with EGARCH and GARCH-In-Mean models

	1st Shortest		**2nd Shortest**		**3rd Shortest**		**4th Shortest**	
Panel D: AR / EGARCH(1,1)								
	N	**T**	**N**	**T**	**N**	**T**	**N**	**T**
c	-0.002	-0.0002	-0.001	-0.0001	-0.001	0.0009	0.0002	0.002
	(-1.13)	(-0.126)	(-0.63)	(-0.152)	(-0.508)	(0.473)	(0.092)	(0.69)
AR(1)	**0.273***	**0.292***	**0.28***	**-0.313***	0.158	**0.235****	0.088	0.06
	(3.753)	(3.237)	(3.166)	(-4.98)	(1.796)	(2.242)	(1.84)	(1.366)
AIC	-1488.07	-2124.74	-1482.48	-2314.03	-1519.05	-2166.42	-1400.67	-2014.05
BIC	-1460.58	-2099.37	-1454.99	-2286.54	-1491.56	-2141.05	-1373.18	-1984.48
Adj. R^2	0.0545	0.0344	0.0305	0.6837	0.0070	0.0166	-0.0055	0.0019
Panel E: AR / GARCH-In-Mean(1,1)								
	N	**T**	**N**	**T**	**N**	**T**	**N**	**T**
c	**-0.006***	**-0.01***	**-0.004****	**-0.002****	**-0.004****	**-0.004****	-0.001	0.0002
	(-3.246)	(-4.883)	(-2.203)	(-1.494)	(-2.352)	(-2.108)	(0.043)	(0.101)
AR(1)	**0.331***	**0.261***	**0.357***	**0.293***	**0.273***	**0.234***	**0.131****	0.083
	(6)	(4.258)	(6.812)	(4.387)	(5.804)	(4.802)	(2.435)	(1.777)
InMean	1.056	2.538	1.361	1.109	1.057	1.185	-0.122	**0.0004**
	(0.477)	(0.801)	(0.716)	(0.516)	(0.615)	(0.462)	(-0.001)	(0.0038)
AIC	-1352.80	-1494.50	-1382.80	-1489.25	-1363.20	-1525.47	-1177.20	-1398.61
BIC	-1341.00	-1482.70	-1371.10	-1477.44	-1351.52	-1513.65	-1165.40	-1386.80
Adj. R^2	0.0611	0.0799	-0.0148	0.0493	0.0395	0.0414	0.0120	0.0086

The entries report results from the estimation of the univariate ARMA with EGARCH and GJR error process and GARCH-In-Mean model specifications for the daily changes of IMAREX Capesize Futures. The estimated coefficients, Newey-West t-statistics in parenthesis, the Akaike and Bayesian information criterion and the adjusted R^2 are reported. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% level. The models have been estimated for the period 5 April 2005 to 29 September 2006.

Table 26

Forecasting IMAREX Capesize with ARMA, VAR and GARCH models

	1st Shortest	**2nd Shortest**	**3rd Shortest**	**4th Shortest**
Panel A: AR(1)				
c	-0.0001	-0.0001	-0.0001	-0.0002
	(-0.071)	(-0.094)	(-0.023)	(-0.079)
AR(1)	**0.264***	**0.225***	**0.167****	**0.131***
	(3.733)	(2.869)	(1.866)	(2.435)
AIC	-1339.70	-1349.42	-1320.01	-1177.16
BIC	-1327.92	-1337.63	-1308.23	-1165.38
Adj. R^2	0.0647	0.0455	0.0229	0.0120
Panel B: VAR(1)				
c	0.0005	0.0003	0.0004	0.0002
	(0.311)	(0.250)	(0.287)	(0.159)
$\Delta F1_{t-1}$	0.039	**0.109****	**0.142****	**0.184***
	(0.503)	(1.859)	(2.077)	(2.697)
$\Delta F2_{t-1}$	0.055	-0.108	-0.07	-0.144
	(0.657)	(-1.362)	(-0.837)	(-1.691)
$\Delta F3_{t-1}$	**0.159****	**0.198****	0.086	**0.152****
	(2.091)	(2.497)	(1.128)	(2.058)
$\Delta F4_{t-1}$	0.06	**0.087****	0.057	0.041
	(1.348)	(1.844)	(1.314)	(1.042)
AIC	-1338.25	-1351.84	-1317.72	-1176.64
BIC	-1318.62	-1332.2	-1298.08	-1157
Adj. R^2	0.0774	0.0682	0.0338	0.0267

Panel C: AR / GARCH(1,1)	**N**	**T**	**N**	**T**	**N**	**T**	**N**	**T**
c	-0.004	0.0004	-0.002	-0.0001	-0.003	0.0008	-0.0002	0.0016
	(-2.216)	(0.228)	(-1.191)	(-0.042)	(-1.637)	(0.405)	(-0.079)	(0.643)
AR(1)	**0.28***	**0.324***	**0.359***	**0.29***	**0.255***	**0.227****	**0.131****	0.083
	(3.75)	(4.029)	(3.469)	(3.229)	(2.278)	(2.203)	(2.435)	(1.77)
AIC	-1488.07	-2154.82	-1482.48	-2124.74	-1519.05	-2166.42	-1400.67	-2014.05
BIC	-1460.58	-2125.22	-1454.99	-2099.37	-1491.56	-2141.05	-1373.18	-1984.48
Adj. R^2	0.0545	0.0507	0.0305	0.0344	0.0070	0.0166	-0.0055	0.0019

The entries report results from the estimation of the univariate ARMA, ARMA with GARCH error process and VAR model specifications for the daily changes of each IMAREX Capesize futures series. The estimated coefficients, Newey-West t-statistics in parenthesis, the Akaike and Bayesian information criterion and the adjusted R^2 are reported. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% level. The models have been estimated for the period 5 April 2005 to 29 September 2006.

Tables 28 – 30 show the in-sample performance of the economic variables, ARMA, VAR and GARCH-family models and the estimated coefficients for the IMAREX Panamax (T/C Basket) Futures.

Table 28 reports the in-sample performance of the economic variables model. The set of the economic variables was augmented with lagged terms of the futures maturity and the Baltic Panamax Index. The table shows the coefficients of the regression, the AIC and BIC values and the adjusted R^2. The R^2 takes the largest value for the shortest futures maturity (6.55%). These values are significantly smaller than the spot rates.

Table 29 presents the in-sample performance for the univariate ARMA models, VAR models and the ARMA models with GARCH error processes for two probability functions. The lag length for the autoregressive and moving average parts are chosen to minimize BIC criterion. We observe that all models seem to have low coefficients of determination. The highest R^2 are referred for the shortest maturity.

Table 30 reports the in-sample performance for the univariate ARMA models with EGARCH and GJR error processes and GARCH-In-Mean models. For our model selection, we choose the lag length that minimizes BIC criterion. These three GARCH-family models are estimated for two alternative conditional probability density functions of the indices returns: Normal distribution and the Student-t distribution.

Table 28

Forecasting IMAREX Panamax Futures with the Economic Variables model

	1st Shortest	2nd Shortest	3rd Shortest	4th Shortest
c	0.003	**0.005****	**0.004****	0.002
	(1.607)	(2.262)	(2.232)	(1.099)
AR(1)	0.074	**0.147****	**0.193***	**0.142***
	(0.906)	(1.902)	(3.61)	(2.92)
BPI_{t-1}	0.102	-0.112	-0.174	-0.094
	(0.592)	(-0.88)	(-1.692)	(-0.838)
GN_{t-1}	-0.0008	-0.002	0.0004	0.001
	(-0.539)	(-1.535)	(0.378)	(0.667)
i_{t-1}	-0.01	**-0.019****	**-0.018****	-0.008
	(-0.998)	(-2.112)	(-2.33)	(-0.93)
ys_{t-1}	-0.006	-0.006	-0.005	-0.005
	(-1.371)	(-1.322)	(-1.297)	(-1.096)
AIC	-1367.70	-1368.80	-1455.1	-1316.45
BIC	-1340.21	-1341.31	-1417.6	-1289.90
Adj. R^2	0.0122	0.0393	0.0564	0.0167

The entries report results from the estimation of the economic variables models for the daily changes of the IMAREX Panamax Futures. AR: a lagged term of IMAREX Panamax Futures, BPI: spot returns of BPI, c : a constant, GN: the log-returns of the S&P GSCI Grain Index, ys: the slope of the yield curve calculated as the difference between the prices of the ten year U.S. government bond and the one-month interbank rate. The estimated coefficients, Newey-West t-statistics in parenthesis, the Akaike and Bayesian information criterion and the adjusted R^2 are reported. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% level. The models have been estimated for the period 5 April 2005 to 29 September 2006.

These models also have low adjusted R^2 values, even negative. Similar to the IMAREX Capesize futures, low values of the R^2 that there is a weakly predictable pattern for the IMAREX Panamax Futures.

Table 29

Forecasting IMAREX Panamax Futures with ARMA, VAR and GARCH models

	1st Shortest	**2nd Shortest**	**3rd Shortest**	**4th Shortest**
Panel A: AR(1)				
c	-0.0001	-0.0001	0.0001	-0.0001
	(-0.084)	(-0.009)	(0.033)	(-0.008)
AR(1)	0.092	**0.153****	**0.199***	**0.145***
	(1.155)	(1.985)	(3.78)	(3.225)
AIC	-1368.25	-1372.53	-1440.45	-1320.02
BIC	-1356.46	-1352.90	-1428.67	-1308.23
Adj. R^2	0.0031	0.0437	0.0346	0.0159
Panel B: VAR(1)				
c	-0.0002	-0.0001	0.0001	-0.0001
	(-0.112)	(-0.026)	(0.038)	(-0.016)
$\Delta F1_{t-1}$	-0.163	(-0.0794)	-0.047	0.0006
	(-1.595)	(-0.901)	(2.077)	(0.009)
$\Delta F2_{t-1}$	0.273	-0.005	0.13	0.049
	(1.586)	(-0.064)	(1.636)	(0.496)
$\Delta F3_{t-1}$	-0.002	0.228	0.046	0.124
	(2.091)	(1.748)	(0.52)	(1.15)
$\Delta F4_{t-1}$	**0.095****	0.068	0.082	0.04
	(1.859)	(1.248)	(1.553)	(0.951)
AIC	-1380.76	-1365.06	-1435.5	-1315.92
BIC	-1361.12	-1345.42	-1415.86	-1296.28
Adj. R^2	0.0528	0.0365	0.0390	0.0218

Panel C: AR / GARCH(1,1)	**N**	**T**	**N**	**T**	**N**	**T**	**N**	**T**
c	0.001	0.0002	-0.0001	-0.0001	0.0002	0.0006	-0.0001	0.001
	(0.7)	(0.228)	(-0.049)	(-0.007)	(0.135)	(0.369)	(-0.001)	(0.643)
AR(1)	0.116	**0.185****	**0.248***	**0.207***	**0.203***	**0.202***	**0.149***	**0.1****
	(1.412)	(4.029)	(2.855)	(2.512)	(3.837)	(3.817)	(3.302)	(1.77)
AIC	-1395.97	-1539.55	-1374.70	-1472.64	-1453.38	-1486.76	-1316.30	-1431.20
BIC	-1376.33	-1515.98	-1355.06	-1449.08	-1433.75	-1463.19	-1296.67	-1407.64
Adj. R^2	-0.0046	-0.0138	0.0037	0.0072	0.0293	0.0265	0.0106	0.0048

The entries report results from the estimation of the univariate ARMA, ARMA with GARCH error process and VAR model specifications for the daily changes of each IMAREX Panamax futures series. The estimated coefficients, Newey-West t-statistics in parenthesis, the Akaike and Bayesian information criterion and the adjusted R^2 are reported. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% level. The models have been estimated for the period 5 April 2005 to 29 September 2006.

Table 30
Forecasting IMAREX Panamax with EGARCH, GJR and GARCH-In-Mean models

	1st Shortest		2nd Shortest		3rd Shortest		4th Shortest	
Panel D: AR / EGARCH(1,1)								
	N	**T**	**N**	**T**	**N**	**T**	**N**	**T**
c	0.0005	0.0006	-0.001	-	0.0001	0.0007	-0.0003	0.001
	(0.282)	(0.369)	(-0.63)	-	(0.058)	(0.423)	(-0.153)	(0.651)
AR(1)	0.103	**0.197****	**0.225***	**-**	**0.195***	**0.2***	**0.128***	**0.101****
	(1.272)	(2.128)	(2.668)	-	(3.72)	(3.774)	(2.89)	(2.319)
AIC	-1394.59	-1541.40	-1384.08	-	-1448.12	-1485.19	-1316.42	-1433.42
BIC	-1371.03	-1513.91	-1360.52	-	-1424.56	-1457.70	-1292.86	-1405.93
Adj. R^2	-0.0055	-0.0194	0.0049	-	0.0267	0.0237	0.0075	0.0021
Panel E: AR / GJR(1,1)								
	N	**T**	**N**	**T**	**N**	**T**	**N**	**T**
c	0.0009	0.0001	-	0.0001	0.0005	0.0008	-	-
	(0.477)	(0.015)	-	(0.098)	(0.298)	(0.477)	-	-
AR(1)	0.104	**0.188****	**-**	**0.2****	**0.208***	**0.2***	**-**	**-**
	(1.282)	(2.068)	-	(2.446)	(3.919)	(3.77)	-	-
AIC	-1395.35	-1538.88	-	-1473.77	-1452.76	-1488.34	-	-
BIC	-1371.78	-1511.39	-	-1446.28	-1429.19	-1460.85	-	-
Adj. R^2	-0.0060	-0.0173	-	0.0052	0.0265	0.0236	-	-
Panel G: AR / GARCH-In-Mean(1,1)								
	N	**T**	**N**	**T**	**N**	**T**	**N**	**T**
c	**0.005***	**0.006***	**0.009***	**0.001**	0.001	**0.003****	-0.0006	**0.015***
	(2.736)	(3.397)	(5.232)	(0.934)	(0.755)	(2.107)	(-0.308)	(7.293)
AR(1)	0.115	**0.186****	**0.24***	**0.206****	**0.202***	**0.2***	**0.145***	0.087**
	(1.397)	(2.035)	(2.807)	(2.503)	(3.839)	(3.815)	(3.225)	(2)
InMean	-3.358	-2.964	-6.922	-1.078	-0.979	-2.54	**0.367***	-1.334
	(-0.949)	(-1.229)	(-0.706)	(-0.448)	(-0.194)	(-0.86)	(9.632)	(-0.307)
AIC	-1401.00	-1551.20	-1379.46	-1478.70	-1457.65	-1493.40	-1177.20	-1440
BIC	-1389.20	-1539.40	-1367.69	-1466.90	-1445.80	-1481.60	-1165.40	-1428.23
Adj. R^2	0.0075	0.0044	0.0192	0.0147	0.0346	0.0332	0.0159	0.0130

The entries report results from the estimation of the univariate ARMA with EGARCH and GJR error process and GARCH-In-Mean model specifications for the daily changes of IMAREX Panamax Futures. The estimated coefficients, Newey-West t-statistics in parenthesis, the Akaike and Bayesian information criterion and the adjusted R^2 are reported. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% level. The models have been estimated for the period 5 April 2005 to 29 September 2006.

Tables 31 – 33 present the in-sample performance of the economic variables, ARMA, VAR and GARCH-family models and the estimated coefficients for the IMAREX TD3 (T/C Basket) Futures.

Table 31 shows the in-sample performance of the economic variables model for the four maturities contracts. The set of the economic variables was augmented with lagged terms of the futures maturity and the Dirty Tanker TD3 Index. The table shows the coefficients of the regression, the AIC and BIC values and the adjusted R^2. The R^2 takes almost zero values and are significantly smaller than the spot rates.

Table 31
Forecasting IMAREX TD3 Futures with the Economic Variables model

	1st Shortest	2nd Shortest	3rd Shortest	4th Shortest
C	-0.0004	0.0003	0.001	-0.0006
	(-0.139)	(0.111)	(0.517)	(-0.302)
AR(1)	0.076	0.081	**0.108****	0.085
	(1.839)	(1.184)	(2.237)	(1.716)
$TD3_{t-1}$	**0.177****	0.052	0.049	0.015
	(2.212)	(0.841)	(1.104)	(0.349)
WTI_{t-1}	0.001	0.0018	**0.002****	0.0004
	(1.295)	(1.849)	(2.391)	(0.608)
i_{t-1}	0.001	0.0038	-0.004	0.003
	(0.108)	(0.392)	(-0.557)	(0.427)
ys_{t-1}	0.001	-0.002	-0.001	0.00005
	(0.178)	(-0.484)	(-0.213)	(0.013)
AIC	-1069.95	-1243.20	-1441.4	-1442.60
BIC	-1042.50	-1215.70	-1414	-1415.10
Adj. R^2	0.0186	0.0028	0.0146	-0.0060

The entries report results from the estimation of the economic variables models for the daily changes of the IMAREX TD3 Futures. AR: a lagged term of IMAREX TD3 Futures, TD3: spot returns of TD3, C: a constant, WTI: the log-returns of the WTI Crude oil, ys: the slope of the yield curve calculated as the difference between the prices of the ten year U.S. government bond and the one-month interbank rate. The estimated coefficients, Newey-West t-statistics in parenthesis, the Akaike and Bayesian information criterion and the adjusted R^2 are reported. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% level. The models have been estimated for the period 5 April 2005 to 29 September 2006.

Table 32 presents the in-sample performance for the univariate ARMA models, VAR models and the ARMA models with GARCH error processes for two probability functions for the IMAREX TD3 futures contracts. We observe that all models seem to have really low coefficients of determination.

Table 33 reports the in-sample performance for the univariate ARMA models with EGARCH and GJR error processes and GARCH-In-Mean models. Some of the econometric specifications cannot be calculated. These three GARCH-family models are estimated for two alternative conditional probability density functions of the indices returns: Normal distribution and the Student-t distribution.

Table 32

Forecasting IMAREX TD3 Futures with ARMA, VAR and GARCH models

	1st Shortest	2nd Shortest	3rd Shortest	4th Shortest
Panel A: AR(1)				
C	0.0003	0.0003	0.0002	-0.00007
	()	(0.159)	(0.141)	(-0.043)
AR(1)	**0.13***	0.099	**0.127***	0.091
	(2.905)	(1.518)	(2.714)	(1.867)
AIC	-1071.33	-1247.80	-1444.04	-1449.92
BIC	-1059.55	-1236.02	-1432.26	-1438.14
Adj. R^2	0.0119	0.0045	0.0110	0.0031
Panel B: VAR(1)				
C	0.0003	0.0003	0.0003	-0.0001
	(0.102)	(0.163)	(0.151)	(-0.07)
$\Delta F1_{t-1}$	0.078	0.123	0.097	0.056
	(0.89)	(1.822)	(1.778)	(1.448)
$\Delta F2_{t-1}$	0.011	-0.161	-0.035	0.031
	(0.08)	(-1.477)	(-0.373)	(0.356)
$\Delta F3_{t-1}$	0.114	**0.236****	-0.0002	-0.003
	(0.798)	(2.186)	(-0.003)	(-0.044)
$\Delta F4_{t-1}$	0.04	0.041	0.104	0.044
	(0.425)	(0.447)	(1.507)	(0.67)
AIC	-1065.86	-1252.5	-1442.16	-1446.08
BIC	-1046.22	-1232.86	-1422.52	-1426.44
Adj. R^2	0.0129	0.0335	0.0239	0.0111

Panel C: AR / GARCH(1,1)

	N	T	N	T	N	T	N	T
C	0.0003	-0.002	0.0001	-0.0006	0.0001	-0.0007	-0.0001	-0.0001
	(0.108)	(-0.763)	(0.019)	(-0.293)	(0.041)	(-0.387)	(-0.043)	(-0.071)
AR(1)	**0.131***	**0.154***	0.12	**0.136****	**0.128***	0.08	0.091	0.04
	(2.908)	(3.3)	(1.81)	(2.008)	(2.735)	(1.678)	(1.87)	(0.861)
AIC	-1067.33	-1137.30	-1245.04	-1312.07	-1442.37	-1509.36	-1445.92	-1594.11
BIC	-1047.70	-1113.74	-1225.40	-1288.51	-1422.74	-1485.80	-1426.29	-1570.55
Adj. R^2	0.0066	0.0014	-0.0013	-0.0054	0.0057	-0.0001	-0.0023	-0.0077

The entries report results from the estimation of the univariate ARMA, ARMA with GARCH error process and VAR model specifications for the daily changes of each IMAREX TD3 futures series. The estimated coefficients, Newey-West t-statistics in parenthesis, the Akaike and Bayesian information criterion and the adjusted R^2 are reported. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% level. The models have been estimated for the period 5 April 2005 to 29 September 2006.

Table 33
Forecasting IMAREX TD3 Futures with EGARCH, GJR and GARCH-In-Mean models

	1st Shortest		2nd Shortest		3rd Shortest		4th Shortest	
Panel C: AR / EGARCH(1,1)								
	N	**T**	**N**	**T**	**N**	**T**	**N**	**T**
c	0.0001	-0.002	-0.0006	-	-0.0002	-0.0006	-0.0002	0.0001
	(0)	(-0.748)	(-0.271)	-	(-0.114)	(-0.33)	(-0.166)	(0.101)
AR(1)	**0.115***	**0.128***	0.072	-	**0.126***	0.072	0.08	0.019
	(2.60)	(2.856)	(1.123)	-	(2.681)	(1.5)	(1.655)	(0.414)
AIC	-1076.42	-1136.95	-1245.03	-	-1444.24	-1510.25	-1445.53	-1600.24
BIC	-1052.86	-1109.46	-1221.46	-	-1420.68	-1482.76	-1421.97	-1572.75
Adj. R^2	0.0036	-0.0008	-0.0048	-	0.0028	-0.0035	-0.0052	-0.0131
Panel C: AR / GJR(1,1)								
	N	**T**	**N**	**T**	**N**	**T**	**N**	**T**
c	-0.002	0.0001	-	-0.0006	0.0001	-0.0006	-	-
	(-0.717)	(0.015)	-	(-0.299)	(0.021)	(-0.339)	-	-
AR(1)	**0.135***	**0.188****	**-**	**0.13****	**0.146***	0.077	**-**	**-**
	(2.971)	(2.068)	-	(1.93)	(3.118)	(1.622)	-	-
AIC	-1065.33	-1135.95	-	-1310.62	-1441.55	-1507.69	-	-
BIC	-1041.77	-1108.46	-	-1283.14	-1417.99	-1480.20	-	-
Adj. R^2	0.0039	-0.0006	-	-0.0078	0.0026	-0.0030	-	-
Panel C: AR / GARCH-In-Mean(1,1)								
	N	**T**	**N**	**T**	**N**	**T**	**N**	**T**
c	-0.001	-0.004	**-0.02***	**-0.02***	**-0.012***	**-0.004****	**0.012***	0.0003
	(-0.534)	(-1.635)	(-8.92)	(-9.748)	(-6.575)	(-2.437)	(6.87)	(0.184)
AR(1)	0.131	**0.153***	**0.122****	**0.13****	**0.124***	0.076	**0.104****	0.042
	(2.908)	(3.264)	(1.996)	(2.336)	(2.643)	(1.64)	(2.165)	(0.921)
InMean	0.611	0.727	10	10	10	2.015	-10	-0.112
	(48583.1)	(0.135)	(0.348)	(0.657)	(0.702)	(0.687)	(-0.132)	(-0.136)
AIC	-1072.80	-1143.30	-1250.40	-1320.60	-1448.80	-1515.90	-1450.10	-1600.2
BIC	-1061.00	-1131.50	-1238.70	-1308.80	-1436.40	-1504.10	-1438.40	-1588.40
Adj. R^2	0.0119	0.0090	0.0107	0.0147	0.0173	0.0134	0.0040	0.0013

The entries report results from the estimation of the univariate ARMA with EGARCH and GJR error process and GARCH-In-Mean model specifications for the daily changes of IMAREX TD3 Futures. The estimated coefficients, Newey-West t-statistics in parenthesis, the Akaike and Bayesian information criterion and the adjusted R^2 are reported. One and two asterisks denote rejection of the null hypothesis of a zero coefficient at the 1% and 5% level. The models have been estimated for the period 5 April 2005 to 29 September 2006.

6.2 Out-of-sample Evidence: Statistical Testing

We construct point and 95% interval forecasts following the procedures described above and perform the three metrics for point forecasts and the likelihood ratio for the interval forecasts. Tables 34 and 35 show the results for the four maturities of the IMAREX Capesize futures. Table 34 shows the statistical measures obtained for point forecasts based on the models previously described. We observe that the Mean Correct Prediction measure is smaller than the one on the spot index.

In order to compare the forecasting ability of the models, we perform pairwise comparisons using the Modified Diebold-Mariano test, in order to point out the best performing models. The MDM shows that all models for each maturity series and predictability metrics outperform the random walk model. However, all econometric models have equal forecasting performance. These results stand for all maturities.

In the case of the interval forecasts, Table 35 shows the percentage of observations that fall outside the constructed 95% interval forecasts (Violations). Moreover, we observe that extreme violations occur for the economic variables model and the VAR(1). In the rest of cases we reject the null hypothesis of efficient 95% intervals. However, there are seven cases in which efficient intervals are constructed, mostly for longer maturities. The AR(1) / GARCH-In-Mean – T model seems to construct efficient interval for the Capesize futures.

Table 34

Out-of-sample performance for IMAREX Capesize Futures

	1st Shortest	2nd Shortest	3rd Shortest	4th Shortest
A. Random Walk				
MAE	4.656	4.885	4.488	4.363
RMSE	8.898	7.795	6.534	6.42
B. Economic Variables				
MAE	3.803	4.072	3.731	3.618
RMSE	6.985	6.346	5.44	5.336
MCP	58.82%	58.98%	59.11%	59.25%
C. AR				
MAE	3.701	3.991	3.689	3.547
RMSE	6.977	6.274	5.41	5.297
MCP	61.55%	62.41%	60.4%	60.83%
D. VAR				
MAE	3.622	4.012	3.743	3.611
RMSE	6.815	6.28	5.488	5.351
MCP	65.85%	61.69%	59.97%	59.97%
E. AR / GARCH(1,1) - N				
MAE	3.712	4.016	3.686	3.544
RMSE	6.857	6.268	5.392	5.277
MCP	63.13%	61.41%	58.82%	60.26%
F. AR / GARCH(1,1) - T				
MAE	3.683	3.975	3.67	3.54
RMSE	6.974	6.252	5.382	5.283
MCP	63.85%	60.98%	60.26%	58.82%
G. AR / EGARCH(1,1) - N				
MAE	3.71	4.02	3.67	3.534
RMSE	6.911	6.298	5.382	5.277
MCP	62.12%	61.26%	61.12%	59.97%
H. AR / EGARCH(1,1) - T				
MAE	3.68	3.984	3.667	3.543
RMSE	6.948	6.253	5.38	5.285
MCP	64.13%	60.98%	60.98%	58.68%
I. AR / GARCH(1,1)-in-mean - N				
MAE	4.393	3.947	3.693	3.574
RMSE	11.177	6.188	5.426	5.322
MCP	61.41%	61.98%	60.11%	60.4%
J. AR / GARCH(1,1)-in-mean - T				
MAE	3.734	3.91	3.67	3.558
RMSE	6.904	6.172	5.411	5.315
MCP	62.27%	61.84%	60.55%	58.25%

The mean absolute prediction error (MAE), the root mean square error (RMSE) and the mean correct prediction (MCP) of the direction of change are reported. For the MCP, the null hypothesis of the sign-test is that the model and the random walk perform equally well, against the alternative that the model under consideration performs better. One asterisk denotes rejection of the null hypothesis at 1% significance levels. The models have been estimated recursively for the period 2 October 2006 to 17 July 2009.

Table 35
Statistical efficiency of the interval forecasts for IMAREX Capesize

	1st Shortest	2nd Shortest	3rd Shortest	4th Shortest
A. Economic Variables				
Violations (%)	62.7	63.56	66.57	59.97
LRunc	-	-	-	-
B. AR				
Violations (%)	9.04	10.47	10.62	8.75
LRunc	19.52*	33.89*	35.51*	17.04*
C. VAR				
Violations (%)	44.19	52.51	59.4	54.23
LRunc	-	-	-	-
D. AR / GARCH(1,1) - N				
Violations (%)	6.17	6.46	6.17	4.45
LRunc	1.87**	2.86*	1.87**	0.46
E. AR / GARCH(1,1) - T				
Violations (%)	7.32	5.88	5.6	4.59
LRunc	6.94*	1.08**	0.50	0.25
F. AR / EGARCH(1,1) - N				
Violations (%)	6.17	8.18	6.89	6.6
LRunc	1.87**	12.54*	4.7*	3.43*
G. AR / EGARCH(1,1) - T				
Violations (%)	6.74	6.03	6.6	5.88
LRunc	4.04*	1.45**	3.43*	1.08**
H. AR / GARCH(1,1)-in-mean - N				
Violations (%)	6.74	6.31	6.89	4.73
LRunc	4.04*	2.34**	4.7*	0.11
I. AR / GARCH(1,1)-in-mean - T				
Violations (%)	7.46	5.45	5.45	4.88
LRunc	7.77*	0.29	0.29	0.02

The table reports the percentage of the observations that fall outside the intervals, and the values of Christoffersen's (1998) likelihood ratio test of unconditional coverage (LRunc) for each Baltic Exchange Index. The null hypothesis is that the percentage of times that the actually index prices fall outside the constructed (1-a)% interval forecasts is a%. One and two asterisks denote rejection of the null at 1% and 5% significance level. Results are reported for daily 95% interval forecasts generated by the specific models in each panel. One each day 10.000 bootstrap samples or simulation runs are formed. The models have been estimated recursively for the period 2 October 2006 to 17 July 2009.

Tables 36 and 37 show the results of the statistical testing for the four maturities of the IMAREX Panamax futures. Table 36 shows the statistical metrics obtained for point forecasts based on the models previously described. We observe that the Mean Correct Prediction measure is smaller than the one on the spot index.

In order to compare the forecasting ability of the models, we perform pairwise comparisons using the Modified Diebold-Mariano test, in order to point out the best performing models. The MDM shows that all models for each maturity series and predictability metrics outperform the random walk model. However, as in Capesize futures, all econometric models have equal forecasting performance. All models have equal performance for each maturity contract,

In the case of the interval forecasts, Table 37 shows the percentage of observations that fall outside the constructed 95% interval forecasts (Violations) and the likelihood ratio of unconditional coverage. Moreover, we observe that extreme violations occur for the economic variables model and the VAR(1). In almost all cases we reject the null hypothesis of efficient 95% intervals. However, there are three cases in which efficient intervals are constructed, all three for the shortest maturity.

Table 36
Out-of-sample performance for IMAREX Panamax Futures

	1st Shortest	2nd Shortest	3rd Shortest	4th Shortest
A. Random Walk				
MAE	3.972	4.342	4.314	4.029
RMSE	7.745	6.593	6.316	5.895
B. Economic Variables				
MAE	3.228	3.591	3.582	3.343
RMSE	6.013	5.381	5.158	4.836
MCP	53.52%	51.51%	51.94%	51.94%
C. AR				
MAE	3.102	3.434	3.4	3.289
RMSE	5.919	5.249	4.979	4.75
MCP	54.38%	57.68%	57.39%	56.24%
D. VAR				
MAE	3.093	3.438	3.402	3.224
RMSE	5.838	5.294	5.024	4.721
MCP	58.97%	58.54%	57.68%	60.26%
E. AR / GARCH(1,1) - N				
MAE	3.1	3.444	3.393	3.228
RMSE	5.801	5.239	4.963	4.706
MCP	54.81%	57.53%	58.54%	57.53%
F. AR / GARCH(1,1) - T				
MAE	3.091	3.434	3.395	3.201
RMSE	5.946	5.233	4.97	4.695
MCP	57.1%	55.81%	57.1%	58.54%
G. AR / EGARCH(1,1) - N				
MAE	3.114	3.445	3.388	3.213
RMSE	5.848	5.272	4.963	4.701
MCP	56.24%	56.67%	57.53%	57.25%
H. AR / EGARCH(1,1) - T				
MAE	3.087	-	3.392	3.206
RMSE	5.934	-	4.967	4.697
MCP	56.67%	-	56.81%	58.68%
I. AR / GJR(1,1) - N				
MAE	3.12	-	3.388	-
RMSE	5.822	-	4.961	-
MCP	55.38%	-	57.96%	-
J. AR / GJR(1,1) - T				
MAE	3.083	3.435	3.391	-
RMSE	5.925	5.241	4.966	-
MCP	56.96%	55.67%	56.53%	-
K. AR / GARCH(1,1)-in-mean - N				
MAE	4.213	3.445	3.418	3.239
RMSE	10.498	5.25	5.01	4.725
MCP	52.08%	56.24%	56.96%	56.1%
L. AR / GARCH(1,1)-in-mean - T				
MAE	3.137	3.431	3.42	3.214
RMSE	5.966	5.219	5.004	4.706
MCP	56.81%	55.24%	56.34%	57.82%

The mean absolute prediction error (MAE), the root mean square error (RMSE) and the mean correct prediction (MCP) of the direction of change are reported. For the MCP, the null hypothesis of the sign-test is that the model and the random walk perform equally well, against the alternative that the model under consideration performs better. One asterisk denotes rejection of the null hypothesis at 1% significance levels. The models have been estimated recursively for the period 2 October 2006 to 17 July 2009.

Table 37

Statistical efficiency of the interval forecasts for IMAREX Panamax

	1st Shortest	2nd Shortest	3rd Shortest	4th Shortest
A. Economic Variables				
Violations (%)	75.47	66.71	70.59	67.29
LRunc	-	-	-	-
B. AR				
Violations (%)	7.46	9.90	10.47	9.18
LRunc	7.77*	27.75*	33.89*	20.8*
C. VAR				
Violations (%)	47.78	55.95	61.84	58.68
LRunc	-	-	-	-
D. AR / GARCH(1,1) - N				
Violations (%)	4.59	6.31	6.74	5.74
LRunc	0.25	2.34**	4.04*	0.77**
E. AR / GARCH(1,1) - T				
Violations (%)	6.60	6.03	6.46	5.31
LRunc	3.43*	1.45**	2.86*	0.14
F. AR / EGARCH(1,1) - N				
Violations (%)	6.03	7.46	8.18	5.74
LRunc	1.45**	7.77*	12.54*	0.77**
G. AR / EGARCH(1,1) - T				
Violations (%)	5.45	-	7.03	6.31
LRunc	0.29	-	5.4*	6.31**
H. AR / GJR(1,1) - N				
Violations (%)	5.16	-	7.89	-
LRunc	0.04	-	10.51*	-
I. AR / GJR(1,1) - T				
Violations (%)	6.31	6.74	6.74	-
LRunc	2.34*	4.04*	4.04*	-
J. AR / GARCH(1,1)-in-mean - N				
Violations (%)	5.74	6.60	7.03	6.03
LRunc	0.74**	3.43*	5.4*	1.45**
K. AR / GARCH(1,1)-in-mean - T				
Violations (%)	6.60	5.88	6.46	5.6
LRunc	3.43*	1.08**	2.86*	0.5**

The table reports the percentage of the observations that fall outside the intervals, and the values of Christoffersen's (1998) likelihood ratio test of unconditional coverage (LRunc) for each Baltic Exchange Index. The null hypothesis is that the percentage of times that the actually index prices fall outside the constructed (1-a)% interval forecasts is a%. One and two asterisks denote rejection of the null at 1% and 5% significance level. Results are reported for daily 95% interval forecasts generated by the specific models in each panel. One each day 10.000 bootstrap samples or simulation runs are formed. The models have been estimated recursively for the period 2 October 2006 to 17 July 2009.

Tables 38 and 39 show the results of the statistical testing for the four maturities of the IMAREX TD3 futures. Table 38 shows the statistical metrics obtained for point forecasts based on the models previously described. We observe that the Mean Correct Prediction measure is smaller than the one on the spot index.

In order to compare the forecasting ability of the models, we perform pairwise comparisons using the Modified Diebold-Mariano test, in order to point out the best performing models. The MDM shows that all models for each maturity series and predictability metrics outperform the random walk model. However, all econometric models have equal forecasting performance. All models have equal performance for each maturity contract.

In the case of the interval forecasts, Table 39 shows the percentage of observations that fall outside the constructed 95% interval forecasts (Violations) and the likelihood ratio of unconditional coverage. Moreover, we observe that extreme violations occur for the economic variables model and the VAR(1). We can see that there are twelve cases where we accept the hypothesis of efficient interval forecasts and other three that we marginally reject at 5% significance level. Eleven of the twelve cases are referred at the first and second shortest maturities.

Table 38

Out-of-sample performance for IMAREX TD3 Futures

	1st Shortest	2nd Shortest	3rd Shortest	4th Shortest
A. Random Walk				
MAE	5.316	4.974	4.191	3.313
RMSE	8.572	7.383	6.354	5.186
B. Economic Variables				
MAE	3.956	3.809	3.141	2.463
RMSE	6.508	5.786	4.814	3.9
MCP	42.90%	44.76%	38.59%	37.16%
C. AR				
MAE	3.911	3.668	3.025	2.397
RMSE	6.497	5.688	4.76	3.837
MCP	50.50%	49.07%	40.32%	40.32%
D. VAR				
MAE	4.212	3.951	3.197	2.656
RMSE	6.753	5.93	4.895	4.027
MCP	39.17%	43.19%	39.89%	37.30%
E. AR / GARCH(1,1) - N				
MAE	3.917	3.678	3.051	2.399
RMSE	6.502	5.693	4.773	3.839
MCP	50.22%	49.21%	41.61%	38.88%
F. AR / GARCH(1,1) - T				
MAE	3.945	3.673	3.027	2.395
RMSE	6.531	5.69	4.752	3.834
MCP	49.21%	49.21%	42.61%	40.03%
G. AR / EGARCH(1,1) - N				
MAE	3.905	3.662	-	2.391
RMSE	6.501	5.679	-	3.837
MCP	48.49%	48.92%	-	38.16%
H. AR / EGARCH(1,1) - T				
MAE	-	3.671	3.029	-
RMSE	-	5.686	4.751	-
MCP	-	49.21%	41.75%	-
I. AR / GJR(1,1) - N				
MAE	-	3.671	3.048	2.401
RMSE	-	5.689	4.774	3.841
MCP	-	49.07%	42.61%	40.46%
J. AR / GJR(1,1) - T				
MAE	3.941	3.672	-	-
RMSE	6.528	5.691	-	-
MCP	49.21%	49.21%	-	-
K. AR / GARCH(1,1)-in-mean - N				
MAE	3.949	3.746	3.064	2.532
RMSE	6.531	5.786	4.774	4.1
MCP	48.78%	47.06%	42.75%	41.03%
L. AR / GARCH(1,1)-in-mean - T				
MAE	3.978	3.695	3.044	2.414
RMSE	6.552	5.714	4.742	3.847
MCP	47.78%	49.35%	42.61%	40.03%

The mean absolute prediction error (MAE), the root mean square error (RMSE) and the mean correct prediction (MCP) of the direction of change are reported. For the MCP, the null hypothesis of the sign-test is that the model and the random walk perform equally well, against the alternative that the model under consideration performs better. One asterisk denotes rejection of the null hypothesis at 1% significance levels. The models have been estimated recursively for the period 2 October 2006 to 17 July 2009.

Table 39
Statistical efficiency of the interval forecasts on TD3 Futures

	1st Shortest	2nd Shortest	3rd Shortest	4th Shortest
A. Economic Variables				
Violations (%)	68.87	65.71	82.07	80.49
LRunc	-	-	-	-
B. AR				
Violations (%)	6.89	6.89	6.89	6.6
LRunc	4.7*	4.7*	4.7*	3.43*
C. VAR				
Violations (%)	57.82	55.95	52.65	43.9
LRunc	-	-	-	-
D. AR / GARCH(1,1) - N				
Violations (%)	4.73	5.16	6.74	5.88
LRunc	0.11	0.04	4.04*	1.08**
E. AR / GARCH(1,1) - T				
Violations (%)	4.73	5.02	5.60	5.60
LRunc	0.11	0	0.5**	0.5**
F. AR / EGARCH(1,1) - N				
Violations (%)	5.02	5.88	-	6.17
LRunc	0	1.08**	-	1.87**
G. AR / EGARCH(1,1) - T				
Violations (%)	-	5.02	5.31	-
LRunc	-	0	0.14	-
H. AR / GJR(1,1) - N				
Violations (%)	-	5.88	6.74	6.74
LRunc	-	1.08**	4.04*	4.04*
I. AR / GJR(1,1) - T				
Violations (%)	5.02	5.60	-	-
LRunc	0	0.5**	-	-
J. AR / GARCH(1,1)-in-mean - N				
Violations (%)	5.31	5.02	6.46	5.88
LRunc	0.14	0	2.86*	1.08**
K. AR / GARCH(1,1)-in-mean - T				
Violations (%)	4.88	5.45	5.88	6.03
LRunc	0.02	0.29	1.08**	1.45**

The table reports the percentage of the observations that fall outside the intervals, and the values of Christoffersen's (1998) likelihood ratio test of unconditional coverage (LRunc) for each Baltic Exchange Index. The null hypothesis is that the percentage of times that the actually index prices fall outside the constructed (1-a)% interval forecasts is a%. One and two asterisks denote rejection of the null at 1% and 5% significance level. Results are reported for daily 95% interval forecasts generated by the specific models in each panel. One each day 10.000 bootstrap samples or simulation runs are formed. The models have been estimated recursively for the period 2 October 2006 to 17 July 2009.

6.3 Out-of-sample Evidence: Economic Significance

In the previous section the reported results on point forecasts suggest that there is a weak evidence of a statistically predictable pattern in the evolution of the IMAREX freight futures. However, we found some models that gave efficient 95% interval forecasts. We examine the economic significance of these patterns by performing trading strategies on point and interval forecasts for each futures maturity.

Tables 40 – 45 present the Sharpe Ratio, Leland's Alpha and their respective bootstrapped 95% confidence intervals (CI) for the IMAREX Capesize futures, IMAREX Panamax and the IMAREX TD3 futures for the trading strategies using IMAREX Futures from different maturities.

In Tables 40-41 results of the trading strategies for the IMAREX Capesize Futures are reported based on point and interval forecasts respectively. Table 40 shows that the SR and A_p are significant in all cases for all futures maturities. Therefore, we have profitable trading strategies on the point forecasts. Similarly, table 41 implies that trading strategies on interval forecasts yield economically significant profits for all futures maturities.

In Tables 42-43 results of the trading strategies for the IMAREX Panamax Futures are reported based on point and interval forecasts respectively. As far as the point forecasts are concerned, results of SR and A_p are significantly positive when using the IMAREX contracts for the trading strategies. In all cases, trading strategies are profitable. In table 43, we observe that all cases have significantly positive SR and *Ap* performance measures. Again, performance measures indicate that trading strategies are profitable.

In tables 44-45 performance measures for the trading strategies on point and interval forecasts on the IMAREX TD3 route are reported. In table 44 for trading strategies on point forecasts, it is easily observable that in all cases, except VAR(1), we accept the hypothesis of profitable strategies under the Sharpe Ratio (SR) and the Leland Alpha (*Ap*). Similarly, for the interval forecasts in all cases under the SR and the *Ap* are significant. Thus, we find clear results for profitable trading strategies on the TD3 both based on point and interval forecasts for all maturities.

Table 40
Trading strategy with IMAREX futures based on point forecasts for IMAREX Capesize

IMAREX Capesize (T/C Baslet) Futures				
	1st Shortest	**2nd Shortest**	**3rd Shortest**	**4th Shortest**
A. Economic Variables				
Sharpe Ratio	0.358	0.6139	0.7408	0.6712
95% CI	(0.17, 0.59)	(0.55, 0.70)	(0.67, 0.82)	(0.59, 0.76)
A_p	0.0233	0.0335	0.0336	0.0308
95% CI	(0.013, 0.037)	(0.028, 0.039)	(0.028, 0.039)	(0.025, 0.037)
B. AR(1)				
Sharpe Ratio	0.584	0.7631	0.8053	0.7664
95% CI	(0.47, 0.73)	(0.69, 0.85)	(0.74, 0.88)	(0.69, 0.85)
A_p	0.0348	0.0388	0.0353	0.0336
95% CI	(0.028, 0.041)	(0.033, 0.046)	(0.03, 0.042)	(0.028, 0.039)
C. VAR(1)				
Sharpe Ratio	0.451	0.614	0.759	0.726
95% CI	(0.36, 0.58)	(0.53, 0.71)	(0.69, 0.84)	(0.65, 0.81)
A_p	0.0285	0.0335	0.0341	0.0325
95% CI	(0.017, 0.042)	(0.028, 0.039)	(0.028, 0.04)	(0.027, 0.038)
D. AR / GARCH(1,1) - N				
Sharpe Ratio	0.5993	0.7669	0.8424	0.8058
95% CI	(0.48, 0.75)	(0.70, 0.85)	(0.77, 0.93)	(0.74, 0.88)
A_p	0.0355	0.0389	0.0363	0.0346
95% CI	(0.03, 0.042)	(0.035, 0.045)	(0.03, 0.042)	(0.029, 0.04)
E. AR / GARCH(1,1) - T				
Sharpe Ratio	0.613	0.7642	0.8284	0.6897
95% CI	(0.49, 0.76)	(0.69, 0.85)	(0.76, 0.91)	(0.61, 0.78)
A_p	0.0361	0.0388	0.036	0.0314
95% CI	(0.03, 0.043)	(0.033, 0.045)	(0.03, 0.042)	(0.025, 0.038)
F. AR / EGARCH(1,1) - N				
Sharpe Ratio	0.5992	0.7454	0.8357	0.6713
95% CI	(0.48, 0.75)	(0.67, 0.82)	(0.76, 0.92)	(0.59, 0.76)
A_p	0.0355	0.0382	0.0362	0.0308
95% CI	(0.029, 0.042)	(0.031, 0.045)	(0.03, 0.043)	(0.024, 0.038)
G. AR / EGARCH(1,1) - T				
Sharpe Ratio	0.6072	0.7512	0.8339	0.6756
95% CI	(0.49, 0.76)	(0.68, 0.83)	(0.77, 0.91)	(0.59, 0.76)
A_p	0.0359	0.0384	0.0361	0.0309
95% CI	(0.03, 0.043)	(0.032, 0.045)	(0.03, 0.042)	(0.025, 0.038)
H. AR / GARCH(1,1)-in-mean - N				
Sharpe Ratio	0.5045	0.752	0.8254	0.7653
95% CI	(0.33, 0.70)	(0.68, 0.84)	(0.76, 0.91)	(0.69, 0.85)
A_p	0.0311	0.0384	0.0359	0.0336
95% CI	(0.025, 0.036)	(0.033, 0.044)	(0.03, 0.042)	(0.028, 0.039)
I. AR / GARCH(1,1)-in-mean - T				
Sharpe Ratio	0.5849	0.6502	0.7847	0.6728
95% CI	(0.47, 0.73)	(0.57, 0.77)	(0.72, 0.87)	(0.60, 0.76)
A_p	0.0349	0.0349	0.0348	0.0308
95% CI	(0.03, 0.043)	(0.025, 0.045)	(0.029, 0.04)	(0.025, 0.038)

The Sharpe ratio (SR), the Leland's alpha (A_p) and their respective bootstrapped 95% confidence intervals (95% CI) in parentheses. The strategy is based on point forecasts obtained from all models for IMAREX Capesize Futures.

Table 41
Trading strategy with IMAREX futures based on interval forecasts for IMAREX Capesize

IMAREX Capesize (T/C Baslet) Futures				
	1st Shortest	**2nd Shortest**	**3rd Shortest**	**4th Shortest**
A. Economic Variables				
Sharpe Ratio	0.6048	0.7625	0.8347	0.8156
95% CI	(0.49, 0.76)	(0.69, 0.85)	(0.77, 0.92)	(0.73, 0.91)
A_p	0.0356	0.0385	0.0361	0.0348
95% CI	(0.024, 0.046)	(0.033, 0.046)	(0.031, 0.042)	(0.025, 0.046)
B. AR(1)				
Sharpe Ratio	0.574	0.7144	0.7706	0.729
95% CI	(0.47, 0.73)	(0.65, 0.78)	(0.70, 0.87)	(0.66, 0.82)
A_p	0.0342	0.037	0.0345	0.0325
95% CI	(0.024, 0.042)	(0.032, 0.044)	(0.025, 0.045)	(0.024, 0.041)
C. VAR(1)				
Sharpe Ratio	0.6162	0.7798	0.8766	0.8514
95% CI	(0.49, 0.77)	(0.70, 0.86)	(0.81, 0.96)	(0.78, 0.93)
A_p	0.0361	0.0391	0.0372	0.0358
95% CI	(0.03, 0.042)	(0.034, 0.047)	(0.031, 0.045)	(0.03, 0.041)
D. AR / GARCH(1,1) - N				
Sharpe Ratio	0.6162	0.7776	0.8751	0.8506
95% CI	(0.49, 0.77)	(0.71, 0.86)	(0.81, 0.96)	(0.78, 0.93)
A_p	0.0361	0.039	0.0371	0.0357
95% CI	(0.03, 0.042)	(0.034, 0.046)	(0.031, 0.045)	(0.03, 0.041)
E. AR / GARCH(1,1) - T				
Sharpe Ratio	0.6143	0.7763	0.8712	0.8423
95% CI	(0.49, 0.77)	(0.70, 0.86)	(0.80, 0.96)	(0.78, 0.92)
A_p	0.036	0.039	0.037	0.0355
95% CI	(0.03, 0.042)	(0.034, 0.046)	(0.031, 0.045)	(0.03, 0.041)
F. AR / EGARCH(1,1) - N				
Sharpe Ratio	0.6192	0.7787	0.877	0.8474
95% CI	(0.49, 0.78)	(0.70, 0.86)	(0.81, 0.96)	(0.78, 0.93)
A_p	0.0362	0.0391	0.0372	0.0357
95% CI	(0.03, 0.042)	(0.034, 0.046)	(0.031, 0.045)	(0.03, 0.041)
G. AR / EGARCH(1,1) - T				
Sharpe Ratio	0.6125	0.7757	0.8743	0.8435
95% CI	(0.49, 0.78)	(0.70, 0.86)	(0.80, 0.96)	(0.78, 0.93)
A_p	0.0359	0.039	0.0371	0.0356
95% CI	(0.03, 0.042)	(0.034, 0.046)	(0.031, 0.045)	(0.03, 0.042)
I. AR / GARCH(1,1)-in-mean - N				
Sharpe Ratio	0.5994	0.7728	0.8719	0.8467
95% CI	(0.48, 0.79)	(0.70, 0.86)	(0.80, 0.95)	(0.78, 0.93)
A_p	0.0354	0.0389	0.037	0.0356
95% CI	(0.03, 0.042)	(0.034, 0.046)	(0.031, 0.045)	(0.03, 0.042)
J. AR / GARCH(1,1)-in-mean - T				
Sharpe Ratio	0.596	0.7453	0.8696	0.8331
95% CI	(0.48, 0.78)	(0.66, 0.84)	(0.80, 0.95)	(0.77, 0.91)
A_p	0.0352	0.038	0.037	0.0353
95% CI	(0.03, 0.041)	(0.033, 0.045)	(0.031, 0.042)	(0.03, 0.041)

The Sharpe ratio (SR), the Leland's alpha (A_p) and their respective bootstrapped 95% confidence intervals (95% CI) in parentheses. The strategy is based on interval forecasts obtained from all models for IMAREX Capesize Futures.

Table 42
Trading strategy with IMAREX futures based on point forecasts for IMARX Panamax

IMAREX Panamax (T/C Baslet) Futures				
	1st Shortest	**2nd Shortest**	**3rd Shortest**	**4th Shortest**
A. Economic Variables				
Sharpe Ratio	0.2944	0.4719	0.3753	0.4497
95% CI	(0.16, 0.47)	(0.35, 0.61)	(0.28, 0.46)	(0.36, 0.54)
A_p	0.0164	0.0228	0.0176	0.0195
95% CI	(0.007, 0.026)	(0.022, 0.032)	(0.012, 0.024)	(0.014, 0.025)
B. AR(1)				
Sharpe Ratio	0.5179	0.7673	0.823	0.5814
95% CI	(0.42, 0.66)	(0.69, 0.86)	(0.76, 0.90)	(0.45, 0.72)
A_p	0.0267	0.0322	0.0315	0.0239
95% CI	(0.022, 0.032)	(0.022, 0.032)	(0.027, 0.036)	(0.017, 0.03)
C. VAR(1)				
Sharpe Ratio	0.3495	0.6213	0.6887	0.7716
95% CI	(0.25, 0.47)	(0.50, 0.77)	(0.60, 0.80)	(0.72, 0.85)
A_p	0.0193	0.0281	0.0282	0.0289
95% CI	(0.015, 0.024)	(0.022, 0.032)	(0.021, 0.036)	(0.021, 0.037)
D. AR / GARCH(1,1) - N				
Sharpe Ratio	0.494	0.7687	0.8466	0.7298
95% CI	(0.39, 0.66)	(0.70, 0.86)	(0.78, 0.92)	(0.64, 0.82)
A_p	0.0257	0.0323	0.0321	0.0279
95% CI	(0.017, 0.037)	(0.022, 0.032)	(0.027, 0.036)	(0.023, 0.033)
E. AR / GARCH(1,1) - T				
Sharpe Ratio	0.5668	0.7493	0.8062	0.752
95% CI	(0.45, 0.74)	(0.67, 0.84)	(0.74, 0.88)	(0.68, 0.82)
A_p	0.0286	0.0317	0.0311	0.0284
95% CI	(0.023, 0.033)	(0.022, 0.032)	(0.027, 0.036)	(0.024, 0.033)
F. AR / EGARCH(1,1) - N				
Sharpe Ratio	0.5498	0.7597	0.831	0.664
95% CI	(0.44, 0.71)	(0.69, 0.85)	(0.77, 0.91)	(0.55, 0.78)
A_p	0.0279	0.032	0.0317	0.0263
95% CI	(0.023, 0.033)	(0.022, 0.032)	(0.028, 0.036)	(0.021, 0.032)
G. AR / EGARCH(1,1) - T				
Sharpe Ratio	0.5632	-	0.8067	0.7338
95% CI	(0.45, 0.73)	-	(0.74, 0.88)	(0.66, 0.81)
A_p	0.0284	-	0.0311	0.028
95% CI	(0.024, 0.033)	-	(0.027, 0.036)	(0.023, 0.033)
H. AR / GJR(1,1) - N				
Sharpe Ratio	0.5122	-	0.837	-
95% CI	(0.40, 0.70)	-	(0.77, 0.91)	-
A_p	0.0264	-	0.0319	-
95% CI	(0.017, 0.037)	-	(0.027, 0.036)	-
I. AR / GJR(1,1) - T				
Sharpe Ratio	0.5653	0.7396	0.8096	-
95% CI	(0.46, 0.73)	(0.67, 0.83)	(0.74, 0.88)	-
A_p	0.0285	0.0315	0.0312	-
95% CI	(0.023, 0.033)	(0.022, 0.032)	(0.027, 0.036)	-
J. AR / GARCH(1,1)-in-mean - N				
Sharpe Ratio	0.3117	0.6755	0.7993	0.6555
95% CI	(0.21, 0.45)	(0.61, 0.77)	(0.74, 0.88)	(0.56, 0.75)
A_p	0.0174	0.0297	0.031	0.026
95% CI	(0.012, 0.023)	(0.022, 0.032)	(0.027, 0.035)	(0.021, 0.031)
K. AR / GARCH(1,1)-in-mean - T				
Sharpe Ratio	0.4877	0.6462	0.742	0.6842
95% CI	(0.33, 0.73)	(0.58, 0.73)	(0.68, 0.81)	(0.62, 0.75)
A_p	0.0255	0.0288	0.0296	0.0268
95% CI	(0.017, 0.036)	(0.022, 0.032)	(0.026, 0.034)	(0.023, 0.031)

The Sharpe ratio (SR), the Leland's alpha (A_p) and their respective bootstrapped 95% confidence intervals (95% CI) in parentheses. The strategy is based on point forecasts obtained from all models for IMAREX Panamax Futures.

Table 43
Trading strategy with IMAREX futures based on interval forecasts for IMAREX Panamax

IMAREX Panamax (T/C Baslet) Futures				
	1st Shortest	**2nd Shortest**	**3rd Shortest**	**4th Shortest**
A. Economic Variables				
Sharpe Ratio	0.5842	0.7799	0.8462	0.8277
95% CI	(0.46, 0.77)	(0.70, 0.87)	(0.78, 0.92)	(0.77, 0.92)
A_p	0.0293	0.0326	0.0321	0.0302
95% CI	(0.023, 0.036)	(0.028, 0.037)	(0.028, 0.037)	(0.023, 0.039)
B. AR(1)				
Sharpe Ratio	0.5531	0.7188	0.7986	0.7781
95% CI	(0.45, 0.71)	(0.65, 0.81)	(0.73, 0.87)	(0.72, 0.86)
A_p	0.0281	0.031	0.0311	0.0291
95% CI	(0.024, 0.032)	(0.028, 0.035)	(0.027, 0.035)	(0.022, 0.037)
C. VAR(1)				
Sharpe Ratio	0.5975	0.8008	0.8708	0.8769
95% CI	(0.48, 0.78)	(0.72, 0.90)	(0.81, 0.95)	(0.82, 0.95)
A_p	0.0298	0.0332	0.0326	0.0312
95% CI	(0.025, 0.035)	(0.029, 0.038)	(0.028, 0.037)	(0.027, 0.036)
D. AR / GARCH(1,1) - N				
Sharpe Ratio	0.5962	0.8034	0.8717	0.8757
95% CI	(0.48, 0.78)	(0.72, 0.90)	(0.81, 0.95)	(0.82, 0.95)
A_p	0.0297	0.0332	0.0326	0.0312
95% CI	(0.025, 0.035)	(0.029, 0.038)	(0.028, 0.037)	(0.027, 0.036)
E. AR / GARCH(1,1) - T				
Sharpe Ratio	0.5971	0.8005	0.8679	0.87
95% CI	(0.48, 0.78)	(0.72, 0.90)	(0.81, 0.95)	(0.81, 0.94)
A_p	0.0298	0.0331	0.0326	0.0311
95% CI	(0.025, 0.035)	(0.029, 0.038)	(0.028, 0.037)	(0.027, 0.036)
F. AR / EGARCH(1,1) - N				
Sharpe Ratio	0.5983	0.7997	0.8707	0.8735
95% CI	(0.48, 0.78)	(0.72, 0.90)	(0.81, 0.95)	(0.82, 0.95)
A_p	0.0298	0.0331	0.0326	0.0311
95% CI	(0.025, 0.035)	(0.029, 0.038)	(0.028, 0.037)	(0.027, 0.036)
G. AR / EGARCH(1,1) - T				
Sharpe Ratio	0.5954	-	0.8684	0.8726
95% CI	(0.48, 0.78)	-	(0.81, 0.95)	(0.82, 0.95)
A_p	0.0297	-	0.0326	0.0311
95% CI	(0.025, 0.035)	-	(0.028, 0.037)	(0.027, 0.036)
H. AR / GJR(1,1) - N				
Sharpe Ratio	0.5974	-	0.8702	-
95% CI	(0.48, 0.78)	-	(0.81, 0.95)	-
A_p	0.0298	-	0.0326	-
95% CI	(0.025, 0.035)	-	(0.028, 0.037)	-
I. AR / GJR(1,1) - T				
Sharpe Ratio	0.595	0.7999	0.8682	-
95% CI	(0.48, 0.78)	(0.72, 0.90)	(0.81, 0.95)	-
A_p	0.0297	0.0331	0.0326	-
95% CI	(0.025, 0.035)	(0.029, 0.038)	(0.028, 0.037)	-
J. AR / GARCH(1,1)-in-mean - N				
Sharpe Ratio	0.5777	0.7983	0.8693	0.8764
95% CI	(0.46, 0.77)	(0.72, 0.90)	(0.81, 0.95)	(0.82, 0.95)
A_p	0.0291	0.0331	0.0326	0.0312
95% CI	(0.023, 0.035)	(0.029, 0.038)	(0.028, 0.037)	(0.024, 0.039)
K. AR / GARCH(1,1)-in-mean - T				
Sharpe Ratio	0.5746	0.7915	0.8566	0.8651
95% CI	(0.46, 0.75)	(0.71, 0.90)	(0.79, 0.94)	(0.82, 0.95)
A_p	0.0289	0.0329	0.0323	0.031
95% CI	(0.025, 0.035)	(0.029, 0.038)	(0.028, 0.037)	(0.023, 0.04)

The Sharpe ratio (SR), the Leland's alpha (A_p) and their respective bootstrapped 95% confidence intervals (95% CI) in parentheses. The strategy is based on interval forecasts obtained from all models for IMAREX Panamax Futures.

Table 44
Trading strategy with IMAREX futures based on point forecasts for IMAREX TD3 Futures

Dirty Tanker TD3 Route Futures				
	1st Shortest	**2nd Shortest**	**3rd Shortest**	**4th Shortest**
A. Economic Variables				
Sharpe Ratio	0.4067	0.3889	0.2678	0.2755
95% CI	(0.35, 0.47)	(0.33, 0.46)	(0.16, 0.38)	(0.21, 0.35)
A_p	0.0243	0.0205	0.0121	0.01
95% CI	(0.02, 0.029)	(0.016, 0.025)	(0.007, 0.018)	(0.007, 0.013)
B. AR(1)				
Sharpe Ratio	0.685	0.7661	0.4787	0.608
95% CI	(0.60, 0.80)	(0.68, 0.87)	(0.39, 0.57)	(0.54, 0.72)
A_p	0.0362	0.034	0.02	0.0192
95% CI	(0.032, 0.04)	(0.03, 0.038)	(0.015, 0.024)	(0.014, 0.025)
C. VAR(1)				
Sharpe Ratio	-0.0406	0.005	-0.0221	-0.0269
95% CI	(-0.12, 0.03)	(-0.07, 0.07)	(-0.10, 0.05)	(-0.11, 0.05)
A_p	-0.0027	0.0003	-0.0011	-0.001
95% CI	(-0.008, 0.002)	(-0.004, 0.005)	(-0.004, 0.002)	(-0.004, 0.002)
D. AR / GARCH(1,1) - N				
Sharpe Ratio	0.6856	0.7609	0.6426	0.6451
95% CI	(0.60, 0.80)	(0.67, 0.86)	(0.53, 0.74)	(0.57, 0.76)
A_p	0.0363	0.0339	0.0248	0.0199
95% CI	(0.032, 0.041)	(0.03, 0.038)	(0.019, 0.03)	(0.015, 0.026)
E. AR / GARCH(1,1) - T				
Sharpe Ratio	0.5845	0.7663	0.6159	0.6452
95% CI	(0.51, 0.67)	(0.68, 0.87)	(0.49, 0.74)	(0.57, 0.76)
A_p	0.0324	0.034	0.0242	0.0199
95% CI	(0.028, 0.037)	(0.03, 0.038)	(0.017, 0.032)	(0.015, 0.026)
F. AR / EGARCH(1,1) - N				
Sharpe Ratio	0.6517	0.7197	-	0.5936
95% CI	(0.57, 0.75)	(0.64, 0.82)	-	(0.51, 0.71)
A_p	0.0349	0.0327	-	0.0187
95% CI	(0.031, 0.039)	(0.029, 0.037)	-	(0.015, 0.022)
G. AR / EGARCH(1,1) - T				
Sharpe Ratio	-	0.7657	0.5729	-
95% CI	-	(0.68, 0.87)	(0.50, 0.68)	-
A_p	-	0.034	0.023	-
95% CI	-	(0.03, 0.038)	(0.019, 0.026)	-
H. AR / GJR(1,1) - N				
Sharpe Ratio	-	0.7369	0.6273	0.6463
95% CI	-	(0.65, 0.84)	(0.56, 0.70)	(0.57, 0.76)
A_p	-	0.0332	0.0245	0.0199
95% CI	-	(0.03, 0.037)	(0.018, 0.032)	(0.015, 0.026)
I. AR / GJR(1,1) - T				
Sharpe Ratio	0.5873	0.7663	-	-
95% CI	(0.51, 0.67)	(0.68, 0.87)	-	-
A_p	0.0326	0.034	-	-
95% CI	(0.028, 0.037)	(0.03, 0.038)	-	-
J. AR / GARCH(1,1)-in-mean - N				
Sharpe Ratio	0.6482	0.6062	0.5596	0.4517
95% CI	(0.57, 0.75)	(0.51, 0.71)	(0.45, 0.68)	(0.36, 0.57)
A_p	0.0348	0.0291	0.0226	0.0153
95% CI	(0.031, 0.039)	(0.253, 0.035)	(0.018, 0.029)	(0.013, 0.018)
K. AR / GARCH(1,1)-in-mean - T				
Sharpe Ratio	0.5346	0.7401	0.4198	0.5756
95% CI	(045, 0.63)	(0.66, 0.84)	(0.25, 0.62)	(0.47, 0.70)
A_p	0.0303	0.0334	0.018	0.0184
95% CI	(0.026, 0.035)	(0.03, 0.038)	(0.012, 0.025)	(0.015, 0.022)

The Sharpe ratio (SR), the Leland's alpha (A_p) and their respective bootstrapped 95% confidence intervals (95% CI) in parentheses. The strategy is based on point forecasts obtained from all models for IMAREX TD3 Futures.

Table 45
Trading strategy with IMAREX futures based on interval forecasts for IMAREX TD3 Futures

Dirty Tanker TD3 Route Futures	1st Shortest	2nd Shortest	3rd Shortest	4th Shortest
A. Economic Variables				
Sharpe Ratio	0.6791	0.7658	0.711	0.6468
95% CI	(0.60, 0.76)	(0.68, 0.88)	(0.64, 0.80)	(0.57, 0.77)
A_p	0.036	0.034	0.0267	0.02
95% CI	(0.032, 0.04)	(0.03, 0.038)	(0.022, 0.031)	(0.015, 0.026)
B. AR(1)				
Sharpe Ratio	0.6311	0.6899	0.6821	0.6585
95% CI	(0.55, 0.73)	(0.61, 0.78)	(0.62, 0.77)	(0.55, 0.79)
A_p	0.0342	0.0319	0.026	0.0203
95% CI	(0.03, 0.038)	(0.028, 0.036)	(0.022, 0.03)	(0.018, 0.023)
C. VAR(1)				
Sharpe Ratio	0.6878	0.7731	0.7192	0.6757
95% CI	(0.60, 0.79)	(0.68, 0.87)	(0.65, 0.81)	(0.60, 0.80)
A_p	0.0363	0.0342	0.0268	0.0205
95% CI	(0.032, 0.04)	(0.03, 0.038)	(0.022, 0.032)	(0.016, 0.027)
D. AR / GARCH(1,1) - N				
Sharpe Ratio	0.6784	0.7718	0.7184	0.6785
95% CI	(0.60, 0.79)	(0.68, 0.88)	(0.65, 0.81)	(0.60, 0.80)
A_p	0.0361	0.0342	0.0269	0.0207
95% CI	(0.032, 0.04)	(0.03, 0.038)	(0.023, 0.033)	(0.016, 0.027)
E. AR / GARCH(1,1) - T				
Sharpe Ratio	0.6803	0.7726	0.7096	0.6715
95% CI	(0.60, 0.79)	(0.69, 0.88)	(0.64, 0.80)	(0.60, 0.79)
A_p	0.0361	0.0343	0.0266	0.0206
95% CI	(0.032, 0.04)	(0.03, 0.038)	(0.022, 0.032)	(0.016, 0.027)
F. AR / EGARCH(1,1) - N				
Sharpe Ratio	0.6813	0.777	-	0.674
95% CI	(0.60, 0.78)	(0.69, 0.88)	-	(0.60, 0.79)
A_p	0.0361	0.0343	-	0.0206
95% CI	(0.032, 0.04)	(0.03, 0.038)	-	(0.016, 0.027)
G. AR / EGARCH(1,1) - T				
Sharpe Ratio	-	0.7728	0.7098	-
95% CI	-	(0.69, 0.88)	(0.64, 0.80)	-
A_p	-	0.0343	0.0266	-
95% CI	-	(0.03, 0.038)	(0.022, 0.032)	-
H. AR / GJR(1,1) - N				
Sharpe Ratio	-	0.7742	0.7177	0.675
95% CI	-	(0.69, 0.87)	(0.65, 0.80)	(0.60, 0.80)
A_p	-	0.0342	0.0268	0.0206
95% CI	-	(0.03, 0.038)	(0.022, 0.033)	(0.016, 0.027)
I. AR / GJR(1,1) - T				
Sharpe Ratio	0.6781	0.7708	-	-
95% CI	(0.59, 0.79)	(0.69, 0.88)	-	-
A_p	0.036	0.0342	-	-
95% CI	(0.032, 0.04)	(0.03, 0.038)	-	-
J. AR / GARCH(1,1)-in-mean - N				
Sharpe Ratio	0.6786	0.7641	0.7193	0.6497
95% CI	(0.60, 0.79)	(0.68, 0.87)	(0.65, 0.81)	(0.54, 0.80)
A_p	0.036	0.034	0.0269	0.02
95% CI	(0.032, 0.04)	(0.03, 0.038)	(0.022, 0.032)	(0.016, 0.027)
K. AR / GARCH(1,1)-in-mean - T				
Sharpe Ratio	0.6748	0.774	0.7112	0.6685
95% CI	(0.59, 0.78)	(0.68, 0.88)	(0.65, 0.81)	(0.60, 0.79)
A_p	0.0359	0.0342	0.0267	0.0204
95% CI	(0.032, 0.04)	(0.03, 0.038)	(0.022, 0.032)	(0.016, 0.027)

The Sharpe ratio (SR), the Leland's alpha (A_p) and their respective bootstrapped 95% confidence intervals (95% CI) in parentheses. The strategy is based on interval forecasts obtained from all models for IMAREX TD3 Futures.

Chapter 7
Conclusion

This dissertation has investigated the forecasting ability of spot and futures freight rates for both dry and tanker markets. In order to answer the question of predictability, we have used the most popular Baltic Exchange Indices and the fast growing IMAREX Freight futures. We have considered up to eleven alternative econometric specifications to identify the ones that provide the most accurate short-term forecasts. We have constructed point and interval forecasts based on the econometric specifications and have evaluated their statistical and economic significance. Economic significance is assessed by trading strategies based on both point and interval forecasts using IMAREX futures.

In the spot freight rates we have found strongly predictable patterns for all Baltic Exchange Indices. Regarding point forecasts, all models outperform the random walk, but all models have statistically equally forecasting performance. In the case of the interval forecasts, we conclude that no model constructs efficient interval forecasts. As far as the economic significance is concerned, point and interval forecasts construct in most cases profitable patterns. We conclude that the results from trading strategies on the TD3 route are profitable even when using longer maturities.

In the futures freight rates we have found weakly predictably patterns in all IMAREX futures series. In the case point forecasts, all models in all futures series and maturities outperform the random walk models. In contrast to the spot freight rates, we conclude that certain model specifications construct efficient 95% interval forecasts. Although weakly predictably patterns are found, results from trading strategies both based on point and interval forecasts indicate economically significant profits.

Results for the spot freight rates imply that participants in the shipping industry, shipowners and charterers, may be able to use the information on the short-term forecasts in order to make business decisions. Furthermore, profitable speculative strategies can be constructed based on point and interval short-term forecasts.

Results for the futures freight rates suggest that the model specifications that are used in the construction of efficient interval forecasts can be used for risk management techniques; for instance, value-at-risk approach. Moreover, profitable strategies can be performed based both on point and interval forecasts.

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